Máster Internacional en
GESTIÓN PESQUERA SOSTENIBLE
(6ª edición: 2015-2017)

TESIS
presentada y públicamente defendida
para la obtención del título de

MASTER OF SCIENCE

A comparison between stock assessment methods and assessment of management scenarios: a practical study case for European hake in GSA's 12 – 16. Calculation of reference points in decreasing trend populations

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Septiembre 2017

Universitat d'Alacant / Universidad de Alicante	GOBIERNO DE ESPAÑA · MINISTERIO DE AGRICULTURA, ALIMENTACIÓN Y MEDIO AMBIENTE	CIHEAM Instituto Agronómico Mediterráneo de Zaragoza

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Esta Tesis fue defendida el día 27 de septiembre de 2017 ante un Tribunal Formado por

- José Luis Sánchez Lizaso

- Maria Grazia Pennino

- José Jacobo Zubcoff

- Bernardo Basurco

Agradecimientos

En primer lugar, me gustaría agradecer al Dr. José Luís Sánchez Lizaso todo su esfuerzo y dedicación a la hora de mantener y organizar el máster. Intentando en todo momento buscar lo mejor para sus alumnos. Sin su ayuda, confianza y transmisión de conocimientos este trabajo no habría sido posible.

En segundo lugar, al Dr. Miguel Bernal por ser un ejemplo de trabajo y profesionalidad a lo largo del pasado año. Transmitiéndome sus conocimientos y permitiendo mi aprendizaje durante las numerosas actividades en las que me ha hecho partícipe en las oficinas de FAO/GFCM y en las numerosas reuniones en las que hemos estado infinitas horas. Él, junto con todo el equipo de la GFCM me han hecho sentir uno más del grupo a lo largo del desarrollo del trabajo permitiéndome evolucionar tanto en el terreno personal cómo en el profesional.

También me gustaría agradecer al Dr. José María Da Rocha la continua disposición a lo largo del desarrollo del proyecto. Pese a las dificultades iniciales siempre ha estado ahí ayudándome con el proyecto y consiguiendo, estando cada uno en una parte del mundo, que la calidad del trabajo no se viese alterada.

Tampoco hay que olvidar todos los expertos que me han ayudado a lo largo de este trabajo. Vita Gancitano proporcionándome los datos ha sido fundamental, así como todos los expertos del WGSAD que me han aportado cada uno su granito de arena a lo largo del desarrollo del proyecto y me han proporcionado ideas para una continua mejora. En especial (aunque también incluida en el personal de la GFCM) a Betulla Morello por animarme y ayudarme en los momentos en los que quería lanzar el ordenador por la ventana. Muchas gracias.

Por último y tal vez más importante, a mi familia por darlo todo durante el pasado año y ayudarme a lo largo de todo mi proceso de formación sacando recursos de dónde no los había. Sin ellos, nada de este trabajo habría sido posible. Han sido parte fundamental de este trabajo y de todos los éxitos futuros.

Muchas gracias a todos.

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Acronyms Table

A4a: Assessment for All

DCRF: Data Collection Reference Framework

F: Fishing Mortality

FAO: Food and Agriculture Organization

F_{lim}: Fishing Mortality Limit

Fmax: Maximum Fishing Mortality

F_{MSY}: Fishing Mortality at Maximum Sustainable Yield

F_{PR}: Precautionary Fishing Mortality

GFCM: General Fisheries Commission for the Mediterranean

GSA: Geographical Subareas

HCR: Harvest Control Rule

H-P: Hodrick and Prescott

ICCAT: International Commission for the Conservation of Atlantic Tunas

ICES: International Council for the Exploration of the Sea

IPCC: Intergovernmental Panel on Climate Change

JRC: Joint Research Center

K: Fish Growth Parameter

L: Length

L_{inf}: Length at Infinite

M: Natural Mortality

MSC: Marine Stewardship Council

MSE: Management Strategy Evaluation

N: Number of Individuals

SAC: Scientific Advisory Committee

SOP: Sum of Squares

SRC-CM: Subregional Committee Central Mediterranean

SSB: Spawning Stock Biomass

STECF: Scientific, Technical and Economic Committee for Fisheries

TSB: Total Spawning Biomass

UNEP/MAP: United Nations Environment Programme

VPA: Virtual Population Analysis

WGHANSA: Working Group on Southern Horse Mackerel, Anchovy and Sardine

WGSA's: Working Group on Stock Assessment

WGSAD: Working Group on Demersal Species

WKMSE: Working Group on Management Strategy Evaluation

XSA: Extended Survival Analysis

Y/R: Yield per Recruit

YPR: Yield per Recruit

Z: Total mortality

Abstract

Global marine fisheries are underperforming economically because of overfishing, pollution and habitat degradation. This fact has serious implications over marine habitats such as latitudinal and in-deep migrations and modifications of the stock – recruitment relationship. It generates a reduction in the number of individuals on fisheries and, subsequently, an increasing number of overexploited stocks.

Nowadays the majority (85 percent) of Mediterranean and Black Sea stocks for which a validated stock assessment exists are fished outside biologically sustainable limits (GFCM, 2016). It is necessary to mitigate the negative impacts over marine fish stocks and improve the state of fish stocks reverting the negative ecological, economic and sociologic effects. Decreasing recruitment trend has also serious negative implications on stock dynamics and, subsequently, affects the accuracy of stock estimates. Stock estimates are the basis for fisheries managers to determine quotas and management regulations.

On one side, the aim of the investigation is to replicate using Assessment for All (a4a) stock assessment tool the last 2016 Working Group on Demersal Species (WGSAD) Extended Survival Analysis (XSA) validated stock assessment for European hake in the Strait of Sicily (GSA's 12-16). Main benefit of using a4a is the capability to introduce an uncertainty parameter in the stock assessment process. It allows to describe better the stock dynamics and, thus, increase the quality of the scientific advice. Also, an assessment of management scenarios was carried on finding possible alternatives in the management of the resource in the Strait of Sicily fishery. Those management scenarios were compared to identify dissimilarities related with the use of different models to assess the stock. On the other side the aim of the investigation is to investigate the implications of decreasing recruitment trends or consider constant recruitment values along the timeseries assessing the consequences along the management process and the calculation of reference points.

Chapter one focuses as an example on the stock of *Merluccius merluccius* (Linnaeus, 1758) in the Strait of Sicily. This fishery was selected due the existence of a subregional multiannual management plan as well as for its economic importance and the fact that hake is considered an emblematic species within the Mediterranean, however subject to the highest overexploitation index (current fishing mortality / target fishing mortality) in the Mediterranean Sea. Chapter two takes as an example *Sardina pilchardus* (Walbaum, 1792) in ICES VIIIc and IXa subareas was use as target stock. We show that ignore recruitment trends ignores part of the risk of managers management strategy. We also show that biomass based harvest control rule decreases the volatility of the stock. No taking care about recruitment trends makes the manager to ignore a slight decreasing of the yield per recruit value. Finally, was noticed that biomass based harvest control rule reduces the risk (measured in probability of biomass bellow 0.5*Bmax) of surpass management boundaries.

Keywords: European Hake, Strait of Sicily, Uncertainty, Stock Assessment, Bioeconomic Modelling, Fisheries Management, Harvest Control Rules, *Sardina pilchardus*.

Resumen

Actualmente, las pesquerías globales sufren un descenso del rendimiento debido a la sobrepesca, contaminación y degradación del hábitat marino. Este hecho tiente implicaciones negativas sobre los hábitats marinos y las pesquerías tales como migraciones latitudinales, migraciones en profundidad y modificación de las relaciones stock reclutamiento. Ello genera una reducción en el número de individuos dentro de las pesquerías y, subsecuentemente, un aumento del número de stocks sobreexplotados.

En este momento la mayoría (85%) de los stocks evaluados en el mar Mediterráneo y Mar Negro para los cuales existe una evaluación pesquera validada se encuentran sobreexplotados (GFCM, 2016). Es necesario mitigar los impactos negativos sobre los stocks pesqueros y mejorar el estado de los mismos reduciendo los efectos ecológicos, económicos y sociales negativos derivados de la actividad pesquera. La tendencia negativa en el reclutamiento también tiene implicaciones negativas en las dinámicas de los stocks y, subsecuentemente, afecta a la precisión de las estimaciones de los stocks. Estas estimaciones son la base para los gestores pesqueros para definir cuotas y estrategias de gestión.

Por una parte, el objetivo de esta investigación es replicar usando "Assessment for all" (a4a) como herramienta de evaluación pesquera la última evaluación pesquera llevada a cabo durante el "2016 Working Group on Demersal Species (WGSAD)" realizado con Extended Survival Analysis (XSA) para la especie merluza europea en el Estrecho de Sicilia (GSA's 12-16). La principal ventaja de utilizar a4a es la capacidad de introducir el parámetro incertidumbre durante el proceso de evaluación pesquera. Ello nos permite describir mejor las dinámicas del stock y, por lo tanto, aumentar la calidad de consejo científico. También se realizó una evaluación de escenarios de gestión para encontrar diferentes alternativas en la gestión del recurso objetivo. Estos escenarios fueron comparados para encontrar similitudes relacionadas con el uso de diferentes modelos para evaluar el stock. Por otro lado, el objetivo de la investigación es investigar las implicaciones de considerar o ignorar la tendencia negativa en una serie de reclutamientos durante los años estudiados evaluando las consecuencias en el proceso de gestión y en el cálculo de los puntos de referencia.

El Capítulo uno se centra en el ejemplo de *Merluccius merluccius* (Linnaeus, 1758) en el Estrecho de Sicilia. La pesquería fue elegida debido a: i) la existencia de un plan de gestión para la merluza europea en la zona de estudio; ii) al alto interés económico que tiene la pesquería; iii) al alto índice de sobreexplotación (F actual / F objetivo) que tiene la pesquería. El Capítulo dos, toma como ejemplo *Sardina pilchardus* (Walbaum, 1792) en las subáreas ICES VIIIc y IXa. A lo largo de la investigación mostramos que: i) ignorar la tendencia en el reclutamiento ignora parte del riesgo de la estrategia de gestión; ii) una HCR basada en biomasa reduce la volatilidad del stock; iii) no tener en cuenta la tendencia en el reclutamiento reduce el valor del rendimiento por recluta en la pesquería; iv) finalmente, una HCR basada en biomasa reduce el riesgo de superar los límites de biomasa marcados por los gestores.

Palabras Clave: Merluza Europea, Estrecho de Sicilia, Incertidumbre, Evaluación pesquera, Modelos bioeconómicos, Gestión Pesquera, Harvest Control Rules, *Sardina pilchardus*.

Chapter 1

A Comparison Between Stock Assessment Methods and Assessment of Management Scenarios: A Practical Study Case for European Hake in GSA's 12 – 16

1.- Introduction

The Mediterranean Sea have sustained important fishing activities since ancient times. Today, after long time of development, semi-industrial and artisanal fleets coexist in the region with many different fishing gears.

This fact, the multispecies component of the fishing activity and the shared stocks by fleets of different countries difficult the management of the Mediterranean resources.

Historically, the fishing activity has been one of the most important economic activities in the Mediterranean region. Due to the multispecies character of the fishing activity in the Mediterranean region, there is a wide variability in the fishing sector. The fleet could be classified by: i) dimension (industrial and artisanal); ii) fishing gear used (depends of the target species).

The fishing sector has a big influence along the Mediterranean Sea. The main reason is that, although the low economical influence in comparison with other sectors, there is a high indirect employment rate around the fishing activity. Is also one of the most important food source for the regional and local communities.

The landings total value at first sale in the Mediterranean and Black Sea is estimated in 3.09$ billions. The subregion with the highest economical value is the Western Mediterranean (1.57$ billions) followed by the Ionian Sea (1.41$ billions), Eastern Mediterranean (1.07$ billions) and Adriatic Sea (0.97$ billions) (GFCM, 2016).

By country, Italy, Algeria, Spain, Tunisia, Greece and Turkey have the most landings percentage in the Mediterranean Sea (Figure 1).

In the Mediterranean region are 2 ways to identify the fishing fleet. By dimension or by fishing gear. With those criteria is possible to do the following classification:

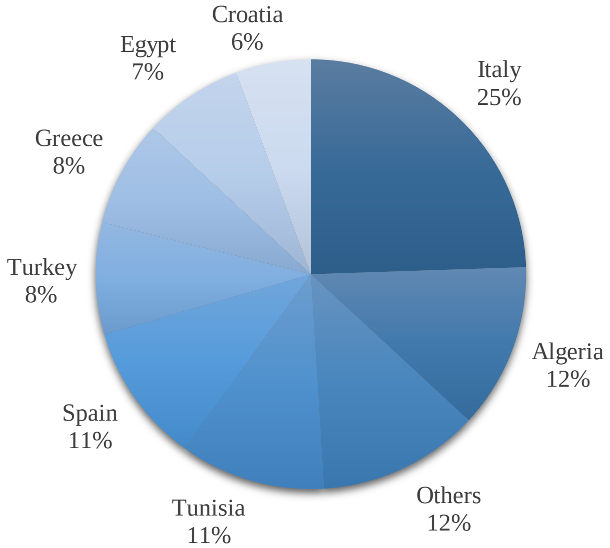


Figure 1 - Landings % in the Mediterranean and Black Sea (Last 10 years), (GFCM, 2016).

- Polyvalent small scale without engine <12m
- Purse Seiners >12m

- Polyvalent small scale with engine <6m
- Polyvalent small scale with engine 6-12m
- Trawlers <12m
- Trawlers 12-24m
- Trawlers >24m
- Purse Seiners 6-12 m
- Long liners >6m
- Pelagic trawlers >6m
- Tuna seiners
- Dredgers >6m
- Polyvalent >12m
- Unlocated

Assessing the fishing sector composition is possible determine that the small-scale vessels in each country are approximately the 80% of the fishing fleet; with the exceptions of Portugal (2 reported vessels), Egypt (20% of small scale fleet over the total country fleet), Spain (40% of small scale fleet over the total country fleet).

In economic terms, the most relevant fishing sectors in number of vessels are the Trawlers (12-24m), purse-seiners (>12m), long liners (>6m) and polyvalent vessels (>12m). Analysing the number of landings, the most important fishing sector are the purse-seiners (41% of the total landings) followed by trawlers (>12m) (14%), polyvalent vessels (>12m) (10%) and small scale polyvalent vessels (6-12m) (9%). (GFCM, 2016).

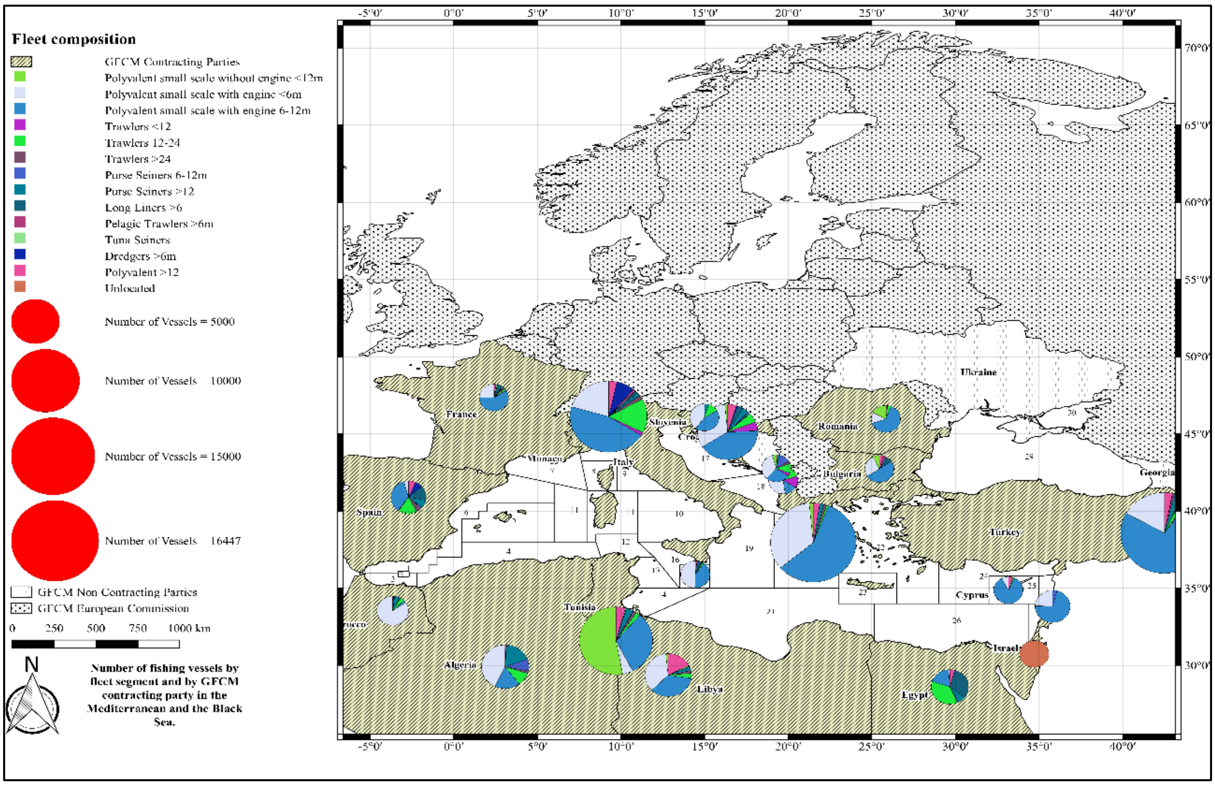


Figure 2 - Overview of fleet composition in the Mediterranean and Black Sea. Data source GFCM, 1016.

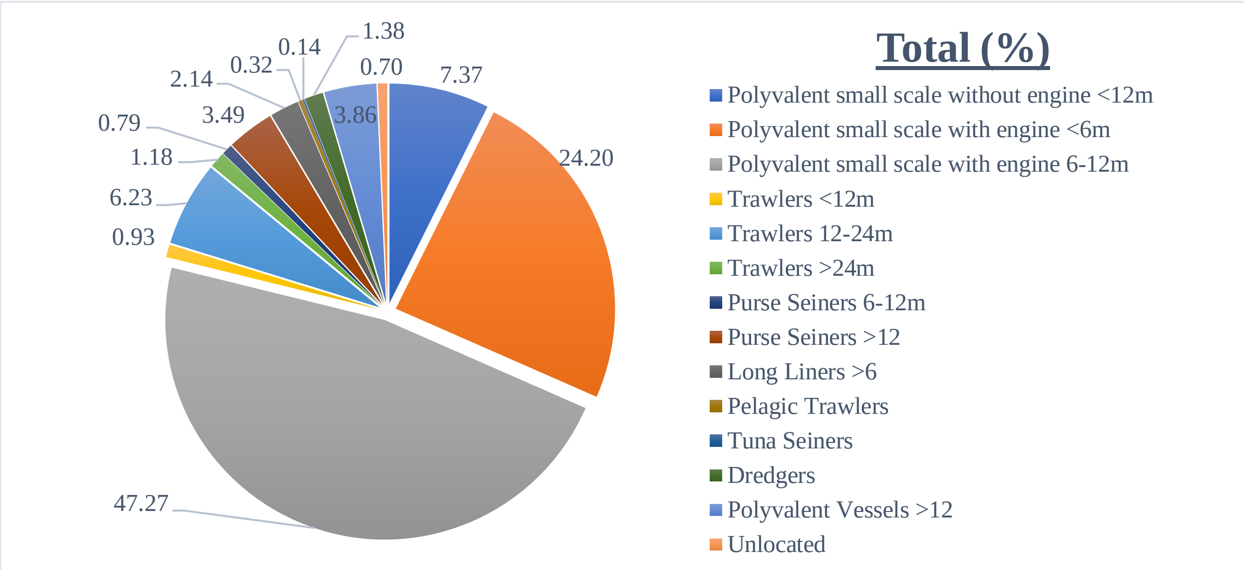


Figure 3 - Mediterranean fleet composition. Data source GFCM 2016.

Counting the catches value, 3 sectors were the most significant: i) Trawlers (>12m) with 38% of the catches value; ii) purse-seiners (>6m) with 27% of the catches value; iii) polyvalent small-scale fleet (>12m) with the 22% of the catches value (GFCM, 2016).

In terms of direct employment, the small-scale fisheries represent the 55% of the total fishing employs in the Mediterranean region.

Nowadays, the sustainability of Mediterranean fisheries is being affected by different threats, including the effects of increased pollution, habitat degradation as result of human activities, introduction of alien species, overfishing and the impacts of the climate change (GFCM, 2016). These are indicators of the need to improve the management in the Mediterranean region in line with an ecosystem approach to the fisheries.

Besides this, the Mediterranean Sea is under serious risks. In the north-western Mediterranean, the littoral areas are being affected by the urbanisation, affecting to the marine productivity. On southern and eastern shores, the increasing population growth is producing an unprecedented anthropic pressure on marine ecosystems (pollution, overfishing, habitat destruction and species introductions). Globally, climate change is one of the most important factors in determining the past and future distributions of biodiversity (Lejeusne et al., 2010) The model observations and theory suggest that marine species respond to ocean warming by shifting their latitudinal and deep range. Such species responses to the anthropic impacts and climate change may lead to local extinction and invasions (Cheung *et al.*, 2009). Altering the natural balance of the ecosystems and resulting in changes in the pattern of marine species richness risking the sustainability of the marine fishing resources. (GFCM, 2016).

1.1.- State and management of Mediterranean fisheries resources

Nowadays approximately the 85% of the assessed Mediterranean stocks are over unsustainable exploitation rates (GFCM 2016). By species, considering the main commercial species in the Mediterranean Sea, is necessary highlight the high fishing pressure over the demersal stocks. Those stocks have higher mortality rates than pelagic stocks (GFCM 2016). Focusing on demersal stocks we should underline the Hake stocks (*Merluccius merluccius*) with an exploitation rates, in average, 5 times higher than the safety biological boundaries; and in some cases, 12 times higher than the target level. This situation doesn't happen in the pelagic stocks, in which ones the exploitation rates are around the target values. Just in two species (*Sprattus sprattus* and *Spicara smaris*) the exploitation rates are below the safety limits.

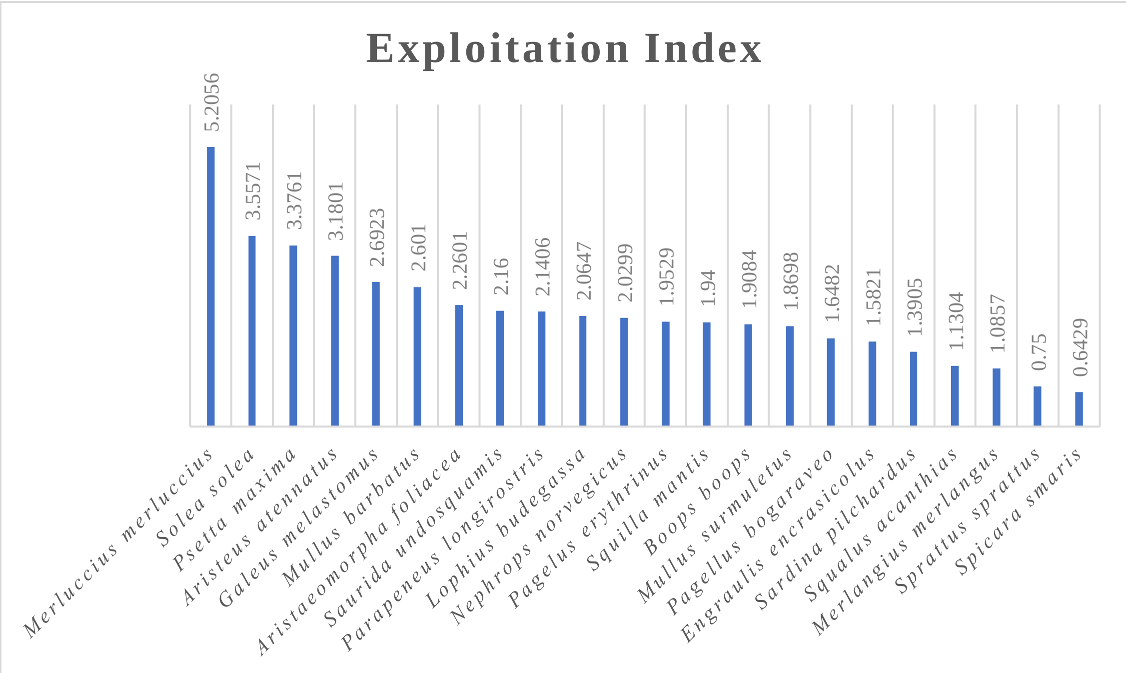


Figure 4 - Average overexploitation index (Fcurr/Ftarget) for the main commercial species in the Mediterranean and Black Sea.

Several regional bodies are working to ensure the sustainability of marine resources in the Mediterranean Sea. Those bodies address several activities related to the management of fisheries and the status of marine environment. Related to fisheries management in the Mediterranean Sea main involved parts are i) the General Fisheries Commission for the Mediterranean (GFCM), ii) the Scientific, Technical and Economic Committee for Fisheries (STECF) and iii) the International Commission for the Conservation of Atlantic Tunas (ICCAT). There are initiatives such as the United Nations Mediterranean Action Plan (UNEP/MAP) and ONG's as OCEANA or Marine Stewardship Council (MSC) to ensure the protection of the marine environment. Those initiatives are focused on i) ensure the sustainable management of natural marine and land resources, ii) protect the environment and coastal zones, iii) strengthen solidarity amongst Mediterranean coastal states and, iv) to contribute to the improvement of the quality of life.

1.2.- The role of the General Fisheries Commission for the Mediterranean (GFCM)

The GFCM is a regional fisheries management organization (RFMO) established under the provisions of Article XIV of the FAO Constitution (FAO). Main objective of the GFCM is to ensure the conservation and the sustainable use (at biological, social, economic and environmental level) of living marine resources in the Mediterranean and in the Black Sea (FAO). Summarizing, GFCM works to provide all countries with an instrument to facilitate them to take better decisions on the management of shared resources.

GFCM is currently composed of 24 members who contribute to its autonomous budget to finance its functioning and 3 Cooperating non-Contracting Parties (GFCM, 2017).

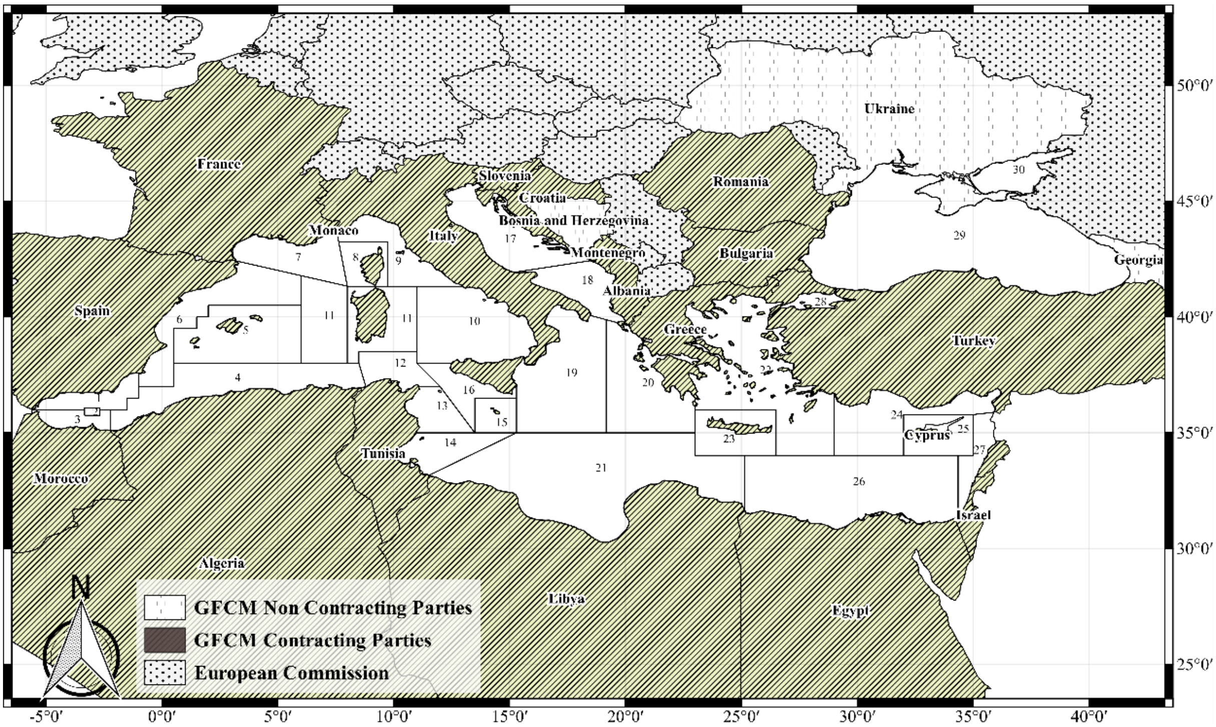


Figure 5 - General Fisheries Commission for the Mediterranean members.

The Commission has the authority to adopt binding recommendations for fisheries conservation and management in its area of application and plays a critical role in fisheries governance in the region. For example, its measures can be related `to the regulation of fishing gears, fishing methods and minimum landing size

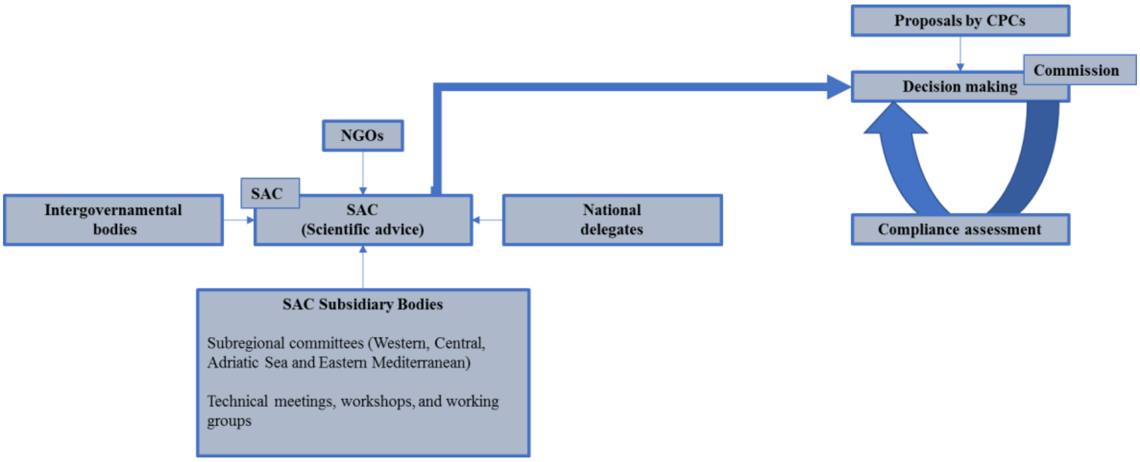


Figure 6 . GFCM provision of advice and decision-making process.

GFCM provides a yearly advice on the state of Mediterranean and Black Sea stocks as well as on other fisheries and marine ecosystems aspects. The advice on the status of stocks is prepared by the Scientific Advisory Committee on Fisheries (SAC) that has recently approved a dedicated strategy to provide advice under two different scenarios: i) when no information or stock assessment is available for a specific management unit; ii) when stock assessment and basic scientific advice is available. The SAC has also proposed to identify priority species for which efforts to collect information and perform stock assessment should be immediately initiated, based on the following criteria: i) shared between different countries; ii) landing volume, iii) landing value; iv) vulnerability. Based on the SAC proposals, the GFCM Members have agreed to identify the following priority species in the different Mediterranean and Black Sea subregions, as follows:

Table 1 - GFCM list of priority species

	Western Mediterranean	Central Mediterranean	Adriatic Sea	Eastern Mediterranean
Pelagic species	*Engraulis encrasicolus*	*Engraulis encrasicolus*	*Engraulis encrasicolus*	*Engraulis encrasicolus*
	Sardina pilchardus	*Sardina pilchardus*	*Sardina pilchardus*	*Sardina pilchardus*
Demersal species	*Parapenaeus longirostris*	*Parapenaeus longirostris*	*Mullus barbatus*	*Mullus barbatus*
	Merluccius merluccius	*Merluccius merluccius*	*Merluccius merluccius*	*Saurida lessepsianus*
	Pagellus bogaraveo	-	-	-
Species of conservation concern	*Anguilla anguilla*			
	Corallium rubrum			

Data limited stock assessment methods has been used to attempt to provide a first advice, including, when possible, using biological and ecological properties from other stocks of the same species subject to fisheries of similar characteristics. The establishment of international surveys under the framework of the FAO has been promoted to collect information on a large number species in a large area (GFCM, WGSAD, 2016).

In addition to the above, the GFCM-SAC considers and proposes generic recommendations addressing issues that are expected to benefit the overall status of stocks. As for example, adjustments on fishing capacity, selectivity, etc.

Concretely, the technical advice on the management of demersal species fisheries in the central Mediterranean, as requested by the Commission, is provided based on the outcomes of these technical activities: i) Working group on demersal species (WGSAD), ii) Working group on management strategy evaluation (WKMSE), iii) Subregional committee central Mediterranean (SRC-CM) to integrate.

When stock assessment and basic scientific advice is available, SAC provides the Commission with the output of simulations on the effect of alternative management scenarios. The working groups on stock assessment attempts to do forecast (short, medium or long term) whenever possible. The subregional committees identifies alternative management scenarios to be tested and attempt Management Strategy Evaluation simulations, if necessary trough specific ad-hoc meetings. The main scenarios to be tested includes: i) Status quo scenario (maintaining current effort/fishing mortality); ii) Achieving F_{MSY} (fishing mortality at maximum sustainable yield) in 2020 or alternative in the medium term; iii) Any other scenario requested by the Commission.

1.2.1.- Working group on demersal species (WGSAD)

The main aim of the activity is to assess the status of demersal resources in the Mediterranean and black sea fisheries.

1.2.2.- Working group on management strategy evaluation (WKMSE)

This working group identifies operational models and management scenarios to compare and evaluate their efficiency (GFCM, WGSAD, 2017).

Is necessary assess the robustness of management strategies to measurements, process errors and model uncertainties (GFCM, WKMSE, 2017).

1.2.3.- Subregional committee central Mediterranean (SRC-CM)

Finally, the SRC-CM integrates all results obtained during the SAC intersessional period with the relevant issues for the subregion, with special attention to the requests of the Commission in relation to the management plans.

1.3.- Structure and objectives of this thesis

Current master thesis has been done in the General Fisheries Commission for the Mediterranean in a framework of collaboration with the University of Alicante. The thesis is integrated in the framework of the GFCM mid-term strategy. The mid-term strategy is based on key actions identified by the GFCM subsidiary bodies an intend to capitalize on accomplishments in the region over recent years in the field of stock assessment and fisheries management, marine environment and control (GFCM, Mid-term Strategy, 2016), (Figure 7).

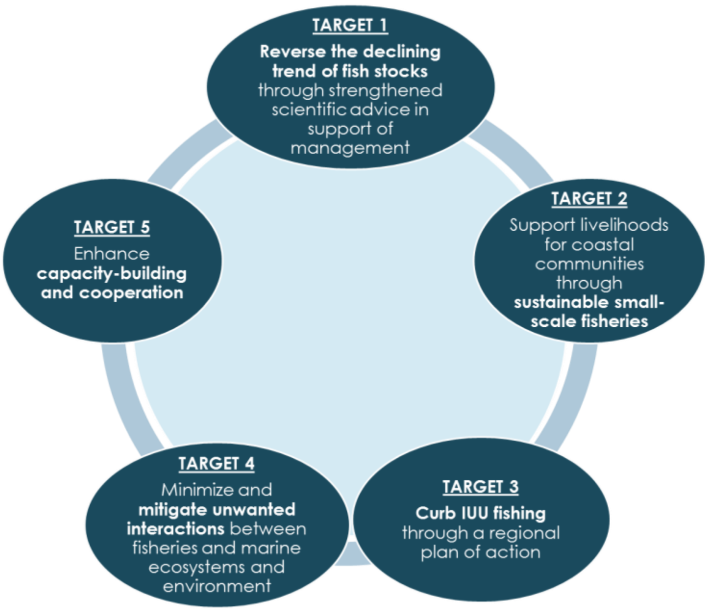


Figure 7 - GFCM Mid-Term Strategy. (GFCM 2016)

Current work is allocated in the GFCM mid-term strategy Target 1 (Reverse the declining trend of fish stock through strengthened scientific advice in support of management). Concretely in the Output 1.3 (Enhance science based GFCM regulations on fisheries management). Nevertheless, the investigation comprises transversally the most of the GFCM Mid-Term Strategy targets.

The goal of the master thesis is to improve management results through a better scientific advice finding alternatives that allow us to incorporate all the potential information.

To achieve the overall objective described above, master thesis was focussed on comparing the 2016 Working Group on Demersal Species (WGSAD) XSA stock assessment validated results for *Merluccius merluccius* in GSAs 12 - 16, with an "Assessment for all" (a4a) stock assessment trying to replicate the validated XSA stock assessment model results for the same target specie in the same study area. A simulation of the short and medium-term effects of alternative management measures was carried out.

The following intermediate objectives were also set-up to address the overall objective of the thesis:

- Compare the replicated a4a stock assessment tool results with the last WGSAD *Merluccius merluccius* validated XSA stock assessment in GSAs 12-16.
- Introduce uncertainty in a4a stock assessment results through the introduction of uncertainty in growth and natural mortality (M) parameters to explain better stock dynamics and increase the quality of the scientific advice.
- Elaborate an assessment of management scenarios (short and medium term) to find possible alternatives in the management of the resource in the study area.
- Compare the simulations of management scenarios (short and medium term) obtained for both stock assessment models to identify possible dissimilarities.

For the development of the work European Hake (*Merluccius merluccius*, Linnaeus, 1758) in GSA 12, 13, 14, 15 and 16 was selected as target species. This fishery was selected due the existence of a subregional multiannual management plan as well as for its economic importance.

2.- Methods

2.1.- Target Stocks and Study area

For the development of the work European Hake (*Merluccius merluccius,* Linnaeus, 1758) in GSA 12, 13, 14, 15 and 16 was selected as target species.

Merluccius merluccius is a demersal fish resource (deep range between 30 – 1075m). The optimal temperature for the target specie is approximately 19ºC. Adults live close to the bottom during day-time, but move off-bottom at night. Adults feed mainly on fish (small hakes, anchovies, pilchard, herrings, cod fishes, sardines and gadoid species) and squids. The young feed on crustaceans (especially euphausiids and amphipods). Are batch spawners. Almost entirely marketed fresh, whole or filleted, to specialized restaurants or retail markets. (FISHBASE, 2017)

A lot of research had been done to identify the stock unit of hake along the strait of Sicily. Which had analysed the most important parameters for stock identification as growth and genetics using a long wide of different technics.

In 1992, Levi *et al.,* compared the growth curves of *Merluccius merluccius* concluding that there are no significant differences to identify two different stocks in the GSA's 13 ,15 & 16.

Lo Brutto *et al.,* (1998) using electrophoresis for isoenzymes identification concluded that the Hake stock in the Strait of Sicily could not be treated as an isolated stock. It's due to Hake is a very good swimmer and it reproduces continuously all over the year by pelagic larvae.

After, Fiorentino *et al.,* (2009) did an update of the previous works doing an electrophoretic, morphometric and growth analyses to test the hypothesis of the existence of an unique hake stock in the Strait of Sicily working area. The detected variation was low between all the sampling points. Although it, they detected some differences at phenotypic level, mainly in females.

Table 2 - Stock unit and main information

Scientific Name:	Common name:	ISCAAP Group:
Merluccius merluccius (Linnaeus, 1758)	European Hake	32
1st Geographical sub-area:	2nd Geographical sub-area:	3rd Geographical sub-area:
GSA 12	GSA 13	GSA 14
4th Geographical sub-area:	5th Geographical sub-area:	6th Geographical sub-area:
GSA 15	GSA 16	
1st Country	2nd Country	3rd Country
Italy	Tunisia	Malta
Stock assessment method:		
XSA	a4a	

Merluccius merluccius is a long live specie with a slow growth rate. Due the economical and biological importance of the target species in the fishery there are wide literature about estimation of growth parameters. Nevertheless, it reveals that growth remains uncertain for hake. Some of the studies carried out are: i) Bouhlal, (1975); ii) Morales-Nin and Aldebert, (1997); iii) Morales-Nin *et al.*, (1998); iv) Morales-Nin and Moranta, (2004); v) Ferraton, (2007); vi) Courbin *et al.*, (2007).

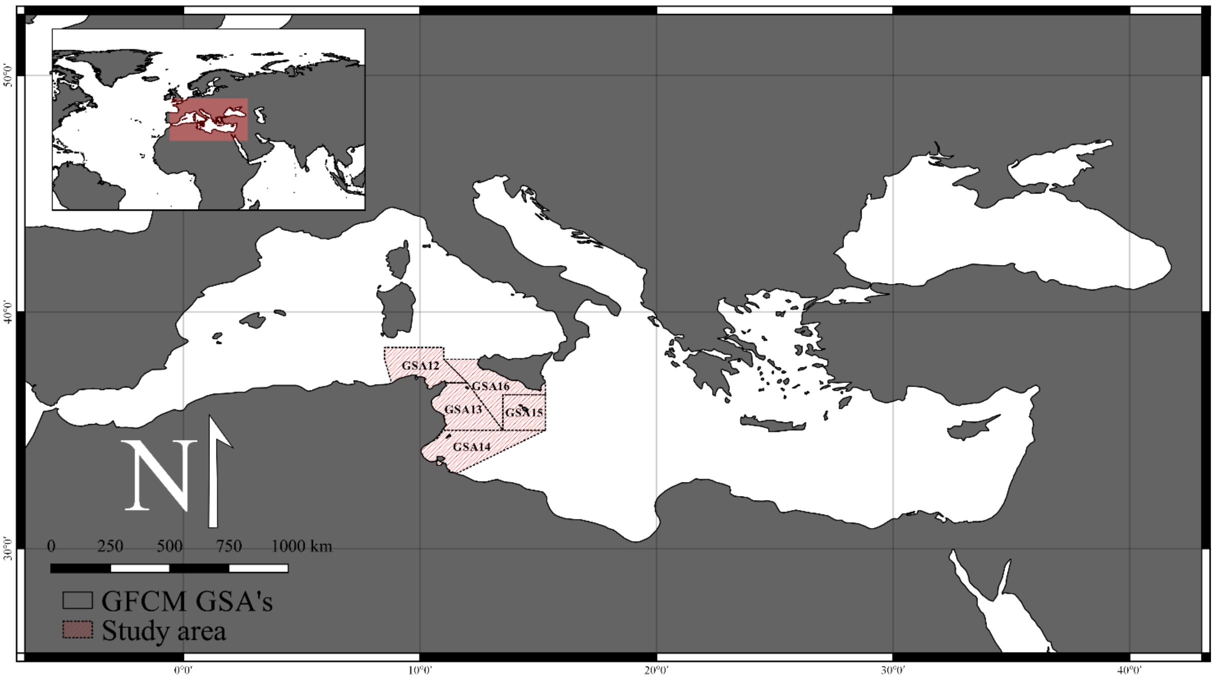


Figure 8 - Study area: GFCM GSA's 12, 13, 14, 15, 16

European hake is an important demersal species for the fisheries in the strait of Sicily (GFCM-GSAs 12-16, south central Mediterranean Sea). It is the main commercial bycatch of trawling targeting deep water rose shrimp and a target species for the artisanal fleet (artisanal long liners and gillnetters). The resource is exploited by 6 main fishing fleet segments: i) Italian coastal trawlers; ii) Italian distant trawlers; iii) Tunisian trawlers; iv) Maltese trawlers; v) Italian vessels using fixed nets; vi) Tunisian vessels using fixed nets. The average of landings of European hake for the period 2007-2015 is over 3000 tons (WGSAD, 2016).

2.2.- Input Data

For the stock assessment realization the following datasets were used: i) Official catch (annual landings and discards, annual size composition of the catch, annual mean weight composition of the catch per individual, annual mean weight composition of the stock per individual, proportion of F mortality before spawning, proportion of M before spawning, proportion of mature individuals); ii) growth parameters; iii) tuning data from Medits surveys in GSA 15 and 16 (years 2007 – 2014); iv) biological parameters estimated by the experts of Tunisia, Malta and Italy. Hake age range was estimated between 0 and 6. Age 6 was used as plus group.

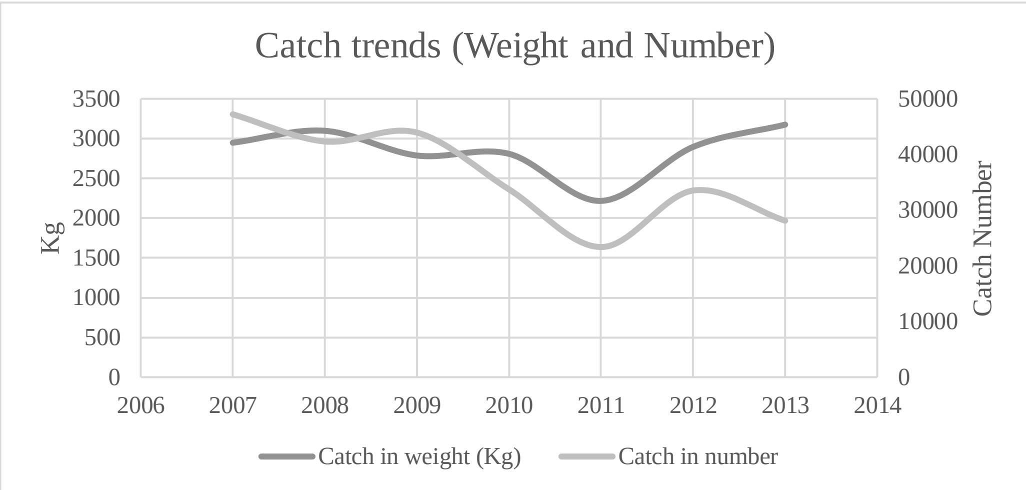


Figure 9 - Catch trends during the timeseries in GSA 12 -16

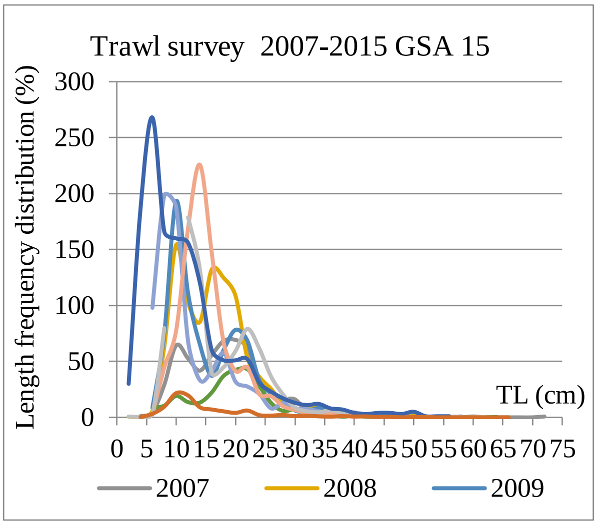
Landings by country for GSA 12,13,14,15 and 16, including Italy, Tunisia and Malta are available since 2006. Landings trends had been constant since 2006 until 2010. There then was a drop in 2011 until 2012. Since 2012 until 2014, when was the record in landings with 4500t in the GSA's 12 to 16. No discard data was provided for the study area and for the target species. Information of capture production is collected annually from relevant offices concerned with fishery statistics, by means of the form GFCM-STATLANT 37A.

The survey is carried out by a scientific trawler boat during May and July. The sample design is stratified with number of haul by stratum proportional to stratum surface (MEDITS, 2012). The gear used is a bottom trawl made of four panels (Fiorentini *et al.*, 1999). The mesh size is 10 mm, which corresponds to, approximately, 20 mm of mesh opening. The sampling depth range is from 10 to 800m.

Since the majority of the *Merluccius merluccius* catches were obtained by trawlers the fishing effort only for that fleet has been described.

Table 3 - Trawl survey sampling area and number of hauls (GSA 16 in 2014)

Stratum	Total Surface (km^2)	Number of hauls
10 – 50 m	2979	11
51 – 100 m	5943	23
101 – 200 m	5565	21
201 – 500 m	6972	27
501 – 800 m	9927	28
Total	31384	120



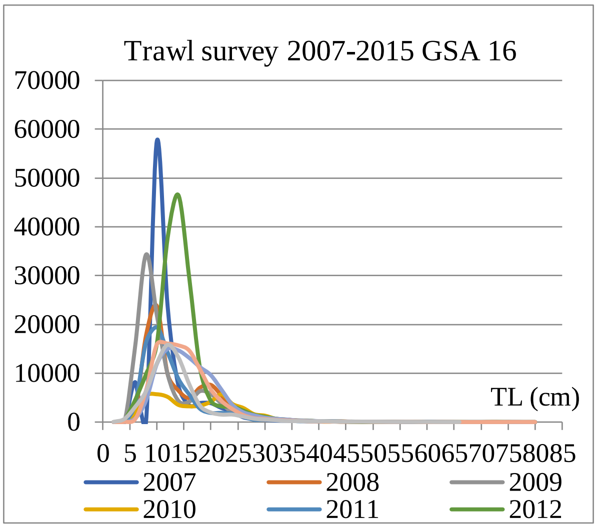


Figure 10 - Length frequency distribution for MEDITS trawl survey 2007-2015 in percentage for GSA 15 (left handed side) and GSA 16 (Right handed side) in number of individuals.

2.3.- Stock assessment methods

Stock assessment are based on virtual population analysis (VPA) modified version. VPA was introduced in fish stock assessment by Gulland (1965) (FAO, 2017). This method is widely used. VPA model has been expanded to include multispecies interactions (Magnusson 1995). VPA is an age structure model that allow us to reconstruct the history of an exploited situation throw the use of catch and natural mortality data. The main outputs of VPA based models are: i) Number of individuals per age and year and ii) Fishing mortality per age and year.

Two different stock assessments methodologies were used in this thesis. Firstly, the last validated stock assessment results of the working group on demersal species for *Merluccius merluccius* in GSA's 12, 13, 14, 15 and 16 were replicated using the same methodology. Secondly, the XSA assessment was reproduced with the assessment for all methodology (a4a) to compare both stock assessment models. Finally, the uncertainty in the growth and natural mortality parameters was introduced in the a4a model to include the observer error in the stock assessment methodology.

2.3.1.- Extended Survival Analysis (XSA)

Extended survival analysis (XSA) (Shepherd, 1992) is a virtual population analysis (VPA) calibration method. XSA fits regressions between abundance-at-age (N) and catch per unit effort (CPUE) for multi-fleet tuning data assuming power functional relationship for recruitment and a constant catchability with respect to time for fully recruited age groups (Daskalov 1998). XSA is less rigid than virtual population analysis method (VPA) about constant exploitation pattern assumption, setting the catchability as constant above certain age. Catchability estimated at certain age is the used to derive abundance estimates to all subsequent ages including the oldest one. The fleet derived population abundance-at-age is used to estimate survivors at the end of the year for each cohort, which later initiate a modified iterated cohort analysis (Daskalov 1998).

Nowadays XSA is one of the most used stock assessment methods in the GFCM area of competence and is the method used historically in the GSA's 12-16 for European hake. Extended survivor analysis was the assessment procedure used in the 2016 WGSAD (GFCM 2016). Although is one of the most used methods, working groups have recommended to stop using this method and start using better suited models.

The last *Merluccius merluccius* GSA 12-16 stock assessment has been replicated during the research. Natural mortality vector was estimated using Prodbiom model (Abella *et al.,* 1998) as done in GFCM-WGSAD 2016. XSA stock assessment was carried out using the FLR R package (Kell *et al.,* 2007).

Min and max F_{bar} has been set as 2 and 4 respectively. Plus group was set at age 6. Preliminary analysis was carried out to explore the input data before the carrying out the stock assessment. A sum of products (SOP) correction was done to assess the ratio (catch number * catch weight)/catch and correct the input data. Twelve different XSA configurations were tested to check the sensitivity of the model against different rage combinations. A single assessment was done with the 12 different rage configurations to evaluate the fitness of each model to the data. Sensitivity analysis with shrinkage values of 0.5, 1, 1.5 and 2 was performed on the results and based on the residuals and retrospective analysis.

Table 4 - XSA algorithm (Shepherd, 1992)

XSA Algorithm

Read data
Introduce main settings
Initialize survivors
Begin iterative loop
   Do VPA (cohort analysis)
   Calculate F, Z, etc
   For each fleet and age
      Calculate weighted mean, reciprocal catchability
      and variance
   Next fleet and age
   Adjusts weights, using the estimated variance of the ln(r)
   For each fleet, age, and year,
      Calculate the estimated populations
   Next fleet, age and year
   For each cohort
      Calculate weighted mean survivors
   Next cohort
Repeat loop
Print results, residuals, diagnostics, etc.

The final assessment used an FLXSA model (Laurence Kell, 2017) fitted to the combined landings data for the period 2007 to 2015. No discards data were provided. This is the same procedure as the agreed at GFCM WGSAD for the previous and current years. The settings are provided in the table below.

```
FLXSA.control.aa4 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30,
min.nse=0.3, fse=1, rage=0, qage=1, shk.n=TRUE, shk.f=TRUE, shk.yrs=3,
shk.ages=3, window=100, tsrange=20, tspower=3, vpa=FALSE)
```

Table 5 - XSA configuration

Catch at age data	2007 – 2015 Ages 1 – 6+
Calibration period	2007 – 2015
Survey: MEDITS	2007 - 2015
Ages	1 - 6
Catchability independent of stock size from:	Age 1
Catchability plateau:	Age 2
Shrinkage	Last 3 years and 3 ages
Shrinkage SE	3
Minimum SE for survivor's estimates	0.3

To check the fitness of the data to the model and to identify possible year or cohort effects diagnostics for the final XSA run were done. The mean natural mortality and fishing mortality were calculated. Finally, a retrospective analysis was ran (Francis & Hilborn 2011).

Historical trends for catch, mean F, SSB (spawning stock biomass) and recruitment were calculated for the final XSA model run.

2.3.2.- Assessment for all (a4a)

A4a is an initiative engaged by the European Commission Joint Research Centre (JRC) aimed at providing a comprehensive and versatile tool to assess all fish stocks harvested in European waters under the remit of the Common Fisheries Policy. The main target of the initiative is to develop a stock assessment method targeting stocks that have a reduced knowledge base on biology ad moderately long-time series on exploitation and abundance. A4a main feature is that the method facilitates the estimation of the current fish stocks and the prediction of their future status under alternative scenarios, essential for the sustainable and profitable management of fisheries (a4a team, European Commission, 2017). Summarizing, a4a aims to provide standard methods for stock assessment and forecasting that can be applied quickly to many stocks in the sea. The main objective of a4a is to promote a risk type of analysis to provide policy and decision makers a perspective of the uncertainty existing on stock assessments and its scenarios being analysed (Jardim *et al.*, 2017).

The process to elaborate the assessment is split in 4 steps:

1º- Convert length data to age data using a growth model

2º- Modelling natural mortality

3º- Assess the stock

4º- MSE

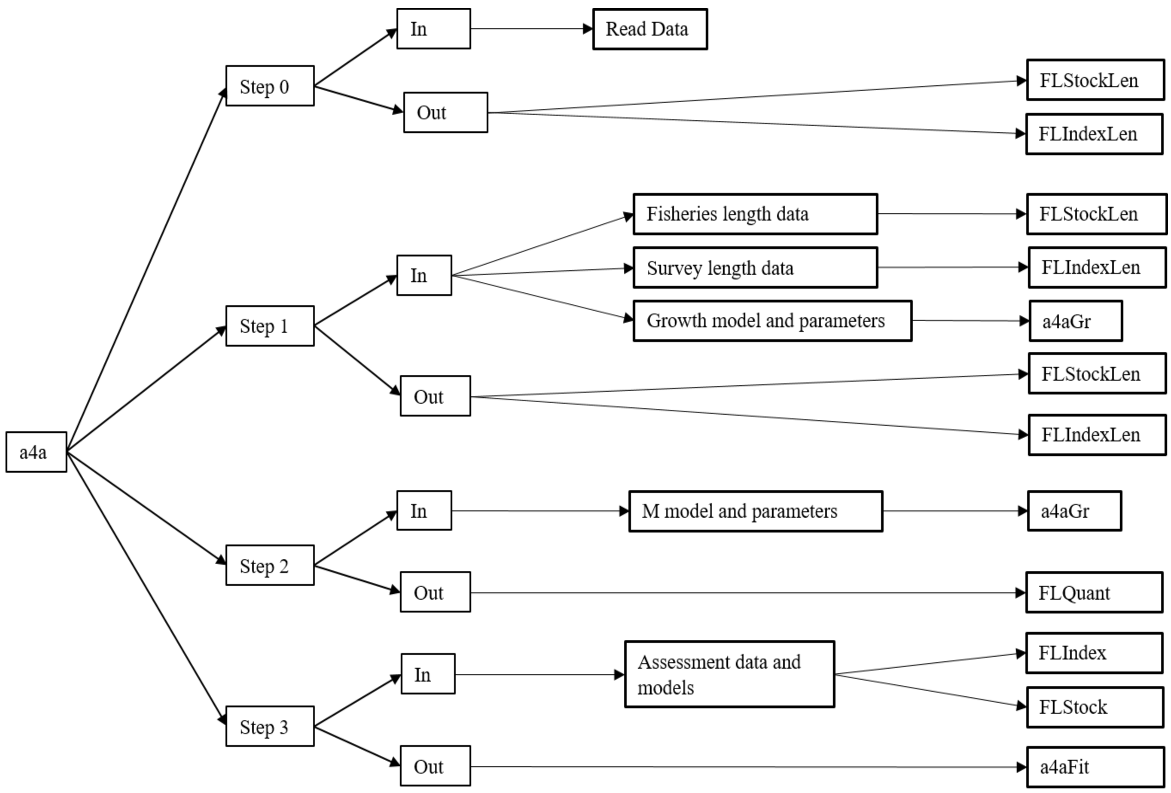


Figure 11 - Process of a4a approach. (Jardim et al., 2017).

In deterministic a4a stock assessment, only the steps 3 and 4 were followed. For the realization of this assessment, steps 1 and 2 were not followed. The sense of it is no fit of growth or natural mortality models. Deterministic stock assessment was done using the same input data that in XSA assessment. The purpose of this method is compare both assessment methodologies and check the differences between the new methodology (a4a) and the one accepted by the working group on demersal species (XSA).

The stock assessment model framework is a non-linear catch-at-age model implemented in R/FLR that can be applied rapidly to a wide range of situations with ow parametrization requirements (Jardim *et al.,* 2017). The a4a stock assessment framework is based on age dynamics.

During the master thesis, we developed a deterministic a4a stock assessment and a stochastic stock assessment. Analysis was done using the same input data that in XSA assessment. During deterministic stock assessment uncertainty was not introduced in the model.

Although, during stochastic a4a, uncertainty was introduced by the iterated calculus of the growth curve, natural mortality parameter and stock recruitment.

Min and max F_{bar} has been set as 2 and 4 respectively. Plus-group was set at age 6. Preliminary analysis was carried out to explore the input data before the carrying out the stock assessment. A sum of products (SOP) correction was done to assess the ratio (catch number * catch weight)/catch and correct the input data. Twelve different XSA configurations were tested to check the sensitivity of the model against different rage combinations. 4, 1 and 2 different catchabilities, fishing mortality and stock recruitment models, respectively, were tested. A single assessment was done with the 8 different combinations to evaluate the fitness of each model to the data.

For fishing mortality, a separable model was used. The model assumed different catchabilities for individuals from 0 to 3 years and from 3 to 6 years. This assumption was done due the selectivity pattern of strait of Sicily trawlers. The target ages for trawlers are until 3 years old. After, older individuals are targeted by longliners due the in-deep migration. For the catchability model, an independent catchability at age was assumed. For the stock recruitment model, an independent of the year stock-recruitment relationship was assumed.

In stochastic a4a, conversion of length structured data to age structured data is performed using growth model. In this case, Von Bertalanffy growth model was used to convert the data. Uncertainty in the growth model was introduced through the inclusion of parameter uncertainty. It was done by making use of the parameter variance-covariance matrix and assuming a multivariate normal distribution (Jardim *et al.,* 2017). The numbers in the variance-covariance matrix could come from the parameter uncertainty from fitting the growth model parameters (Jardim *et al.,* 2017). The variance-covariance matrix was set by scaling a correlation matrix using a cv of 0.2. 250 iterations were simulated to sample randomly the multivariate normal distribution. As an output, 250 data sets were obtained.

$$L(t) = L_{\infty}(1 - e^{-K(t-t_0)})$$ Von Bertalanffy Equation

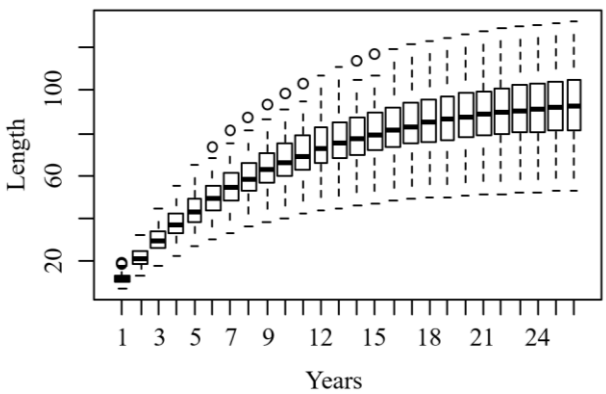


Figure 13 - Growth Curve with a multivariate normal distribution

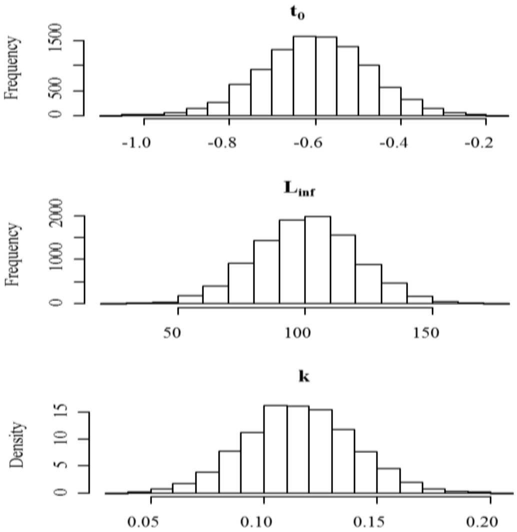


Figure 12 - Marginal distributions of each growth parameter using multivariate normal distribution.

Natural mortality is also one of the main sources of uncertainty in stock assessment (Gislason, *et al.*, 2010). In a4a, natural mortality is dealt as an external parameter to the stock assessment model. The way of modelling is like that of growth (Jardim *et al.*, 2017). Gislasson natural mortality model was used to compute natural mortality. This method is done to avoid the 0.2 assumption in target stock natural mortality.

Once the parameters were estimated a4a stock assessment model was ran. In a4a there are 5 sub models in the operation: i) a model for F at age; ii) a model for the initial age structure; iii) a model for recruitment; iv) a list of models for abundance indices catchability at age; v) a list of models for the observation variance of catch at age and abundance indices (Jardim *et al.*, 2017).

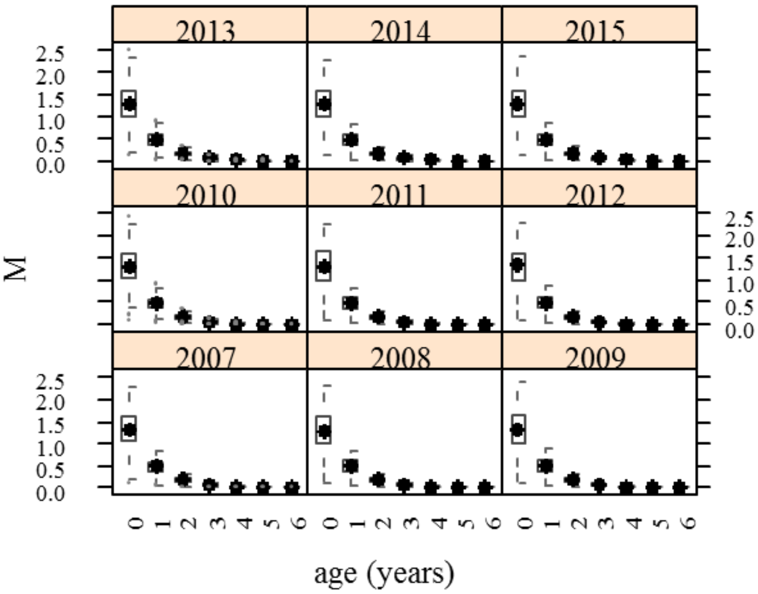


Figure 14 - Natural mortality by age and year

The statistical catch at age model is based on the Baranov catch equation:

$$e^{E[logC_{a\,y}]} = \frac{F_{ay}}{F_{ay} + M_{ay}}(1 - e^{-(F_{ay}+M_{ay})})R_{a=0,y}e^{-\sum(F_{ay}+M_{ay})}$$

And the common survey catchability:

$$e^{E[logI_{a\,y}]} = Q_{ay}R_a e^{-\sum(F_{ay}+M_{ay})}$$

Where

$$C_{ay} \sim LogNormal(E[\log C_{ay}], \sigma_{ay}^2) \qquad I \sim LogNormal(E[\log I_{ay}], \tau_{ay}^2)$$

The likelihood is defined by

$$lc = \sum_{ay}(w_{ay}^{(c)} l_N(\log C_{ay,}\sigma_{ay}^2; \log C_{ay}))$$

$$li = \sum_{s}\sum_{ay}(w_{ays}^{(s)} l_N(\log I_{ays,}\tau_{ays}^2; \log I_{ays}))$$

$$l = l_C + l_I$$

Where M is natural mortality, F fishing mortality, R recruitment, Q survey catchability, C catch and l is the negative log-likelihood of a normal distribution (Jardim, E., *et al.*, 2017). Recruitment is modelled as a fixed variance random effect using the geometric mean model. F model was assumed as year/age separable F model (~factor (age) + factor (year)).

Stock assessment was carried out and reference points were obtained using yield per recruit analysis. As in the previous stock assessments, diagnostics were run to check the fitness of the data.

Table 6 - Summary of data sources by model

Extended survivor analysis (XSA)		**Assessment for all (a4a)**			
Natural Mortality (M)	**Growth Parameters**	**Natural Mortality (M)**		**Growth Parameters**	
Deterministic	**Deterministic**	**Stochastic**	**Deterministic**	**Stochastic**	**Deterministic**
PRODBIOM model	Experts estimations	Iterated multivariate normal distribution + Gislasson (250 iterations)	Prodbiom model	Experts estimations + Iterated Von Bertalanffy model (250 iterations)	Experts estimations

To check the fitness of the data to the model and to identify possible year or cohort effects, diagnostics for the final a4a run were done. The mean natural mortality and fishing mortality were calculated. Finally, a retrospective analysis was run (Francis, R. I. C. C. & Hilborn, R., 2011).

2.4.- Reference Points

Reference points are needed to assess the status of the stocks. It began as conceptual criteria which capture in broad terms the management objective of the fishery (FAO, 2017).

F_{MSY} is the fishing mortality consistent with achieving maximum sustainable yield (MSY). GFCM implemented the MSY (maximum sustainable yield) for providing advice on the exploitation of the stocks. The aim of this approach is to manage all stocks at an exploitation rate (F) that is consistent with maximum long-term yield while providing a low risk to the stock. In the most Mediterranean and Black sea fisheries, due the lack of information, it is not possible the estimation of F_{MSY}, for that reason $F_{0.1}$ is used as a proxy. $F_{0.1}$ is the fishing mortality rate at which the marginal yield-per-recruit is the 10% of the marginal yield-per-recruit on the unexploited stock (ICES advice, 2012). Nowadays, in the Mediterranean and Black Sea fisheries, almost all management strategies currently adopted are limited to the control of fishing capacity effort and/or to the application of technical measures, such as mesh size regulation, establishment of a minimum landing size and closures of areas and seasonal openings (Colloca *et al., 2013*).

Due to the shape of the wield per recruit (YPR) curve, a maximum is often not reached, and F_{max} has therefore not been defined for several years. For that reason, YPR F reference points are not applicable to this stock since F_{max} is undefined in the most years. A $F_{0.1}$ is used as a proxy of the F_{MSY} reference point. F_{MSY} currently, is considered as inestimable using standard equilibrium considerations and would need to be determined as part of a management strategy evaluation.

This is done as an aim to save the stock and reconduct it to achieve the sustainability in the fishery (Figure 15). When the stock is outside the safe fishing area, management measures should be enforced to: i) reduce the effort, ii) spatial closures, iii) protect young or old individuals.

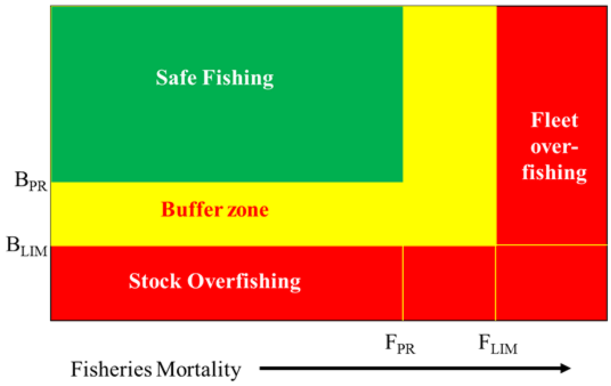


Figure 15 - Sustainability from an advisory point of view.

2.4.1.- Short-Term Forecasts

Short-term prognoses were carried out in FLR using FLCore, projecting the stock forward three years from the last data year (2015) to 2018. The short-term forecasts were developed for the XSA and the deterministic a4a models. The script used was developed by Scott and Osio in 2013.

For those years, many assumptions were made. Weight-at-age in the stock, weight-at-age in the catch and weight at age in the discards are taken to be the average of the last 3 years (geometric mean). The exploitation pattern and the relationship landings-discards were taken to be the mean value of the last 3 years (geometric mean). 22 Different scenarios were tested assuming different F values to see the response of the stock against different management measures. The fist scenario was a total fishery closure (F=0). Then we increased the value of F until F=2. Being the step between scenario and scenario of 0.1. Also, the F_{MSY} scenario (F=0.21) was tested.

Recruitment is one of the main sources of uncertainty during the stock assessment and forecasting process (Myers & Mertz 1998). For the realization of the short-term forecast, the recruitment was calculated as the geometric mean recruitment over the period 2013 - 2015.

2.5.- MSE

Management strategy evaluation (MSE) is widely considered to be the most appropriate way to evaluate the trade-offs achieved by alternative management strategies and to assess the consequences of uncertainty for achieving management goals.

MSE uses simulation testing to determine how robust management strategies are to measurement and process error and to model uncertainty (GFCM WKMSE, 2017)

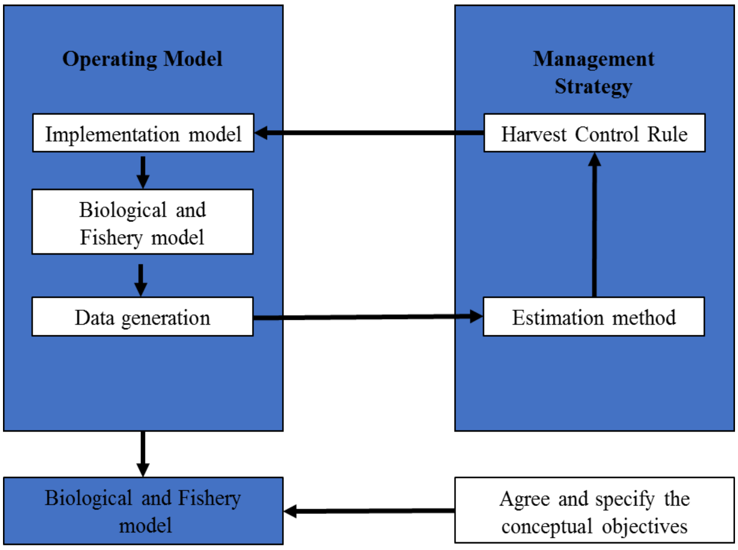


Figure 16 - Conceptual overview of the management strategy evaluation modelling process. Modified from Betulla Morello WKMSE.

The basic steps developed by Punt *et. al.*, 2016, were followed to the MSE development process:

Table 7 - Management strategy evaluation process

1. Identification of the management objectives and representation of these using quantitative statistics.
2. Identification of uncertainties.
3. Development of a set of models which provide a mathematical representation of the system to be managed.
4. Selection of the parameters of the operating model
5. Identification of candidate management strategies which could be implemented
6. Simulation of the application of each management strategy for each operating model
7. Summary and interpretation of the performance statistics.
Management strategy evaluation process (Punt *et. al.*, 2016)

One of the main strengths of MSE is that it brings uncertainty centre stage in the modelling process. Uncertainty plays a fundamental part in the dynamics of ecological and economic systems, in our measurement and understanding of these systems, and in the devising and implementation of rules to control harvesting.

Long term forecasts were also performed with different management scenarios to compare the effectiveness for achieving management objectives of different combinations of data collection, methods of analysis and subsequent processes leading to management measures (New England Fishery Management Council, 2017). MSE can be used to identify the best management strategy among a set of candidate strategies or to determine the quality of the management measure (New England Fishery Management Council, 2017).

As in the previous procedure, the long-term forecast and MSE was done using XSA and a4a (stochastic and deterministic) tools.

Different management measures were tested to see the future effects in the fishery dynamics: i) Status Quo scenario, ii) $F_{0.1}$ as F_{MSY} proxy, iii) 50% Reduction of F, iv) 70% reduction of F, v) 90% reduction of F.

Status quo scenario is keep the fishing mortality of the future projected years as the mean of the last 3 data years. The status quo scenario is useful to assess the future trend of the stock if the same fishing mortality is carried on.

50% fishing mortality reduction scenario is an analysis of contrast scenarios assuming a change of selectivity for strait of Sicily fleet with a reduction of 50% in fishing mortality.

70% fishing mortality reduction scenario simulates a high decreasing of fishing mortality values due a semi-catastrophic event. It is a need-to-recovery management scenario.

90% fishing mortality reduction scenario is an analysis of contrast scenarios assuming a closure in Strait of Sicily fishery simulating an emergency response for a catastrophic emergency.

The forecast was carried until 2037 (24 years forecast). This MSE has been done within the framework of the GFCM Working Group on management strategy evaluation (20 – 23 February 2017). The main aim of the WKMSE was assess biological, economic and social implications of management scenarios in the GFCM area.

3.- Results

3.1.- Stock Assessment

3.1.1.- XSA Results

The main results for the XSA performed with FLR are presented in table 9 to make their comparison easier. It shows the values for recruitment, spawning stock biomass (SSB), catches and fishing mortality for the different XSA configurations. We can see a decreasing trend in the recruitment values and an increasing trend in the spawning stock biomass. In 2011 there was a negative peak in the fishing mortality and subsequently, in catch. All result with different configurations were similar.

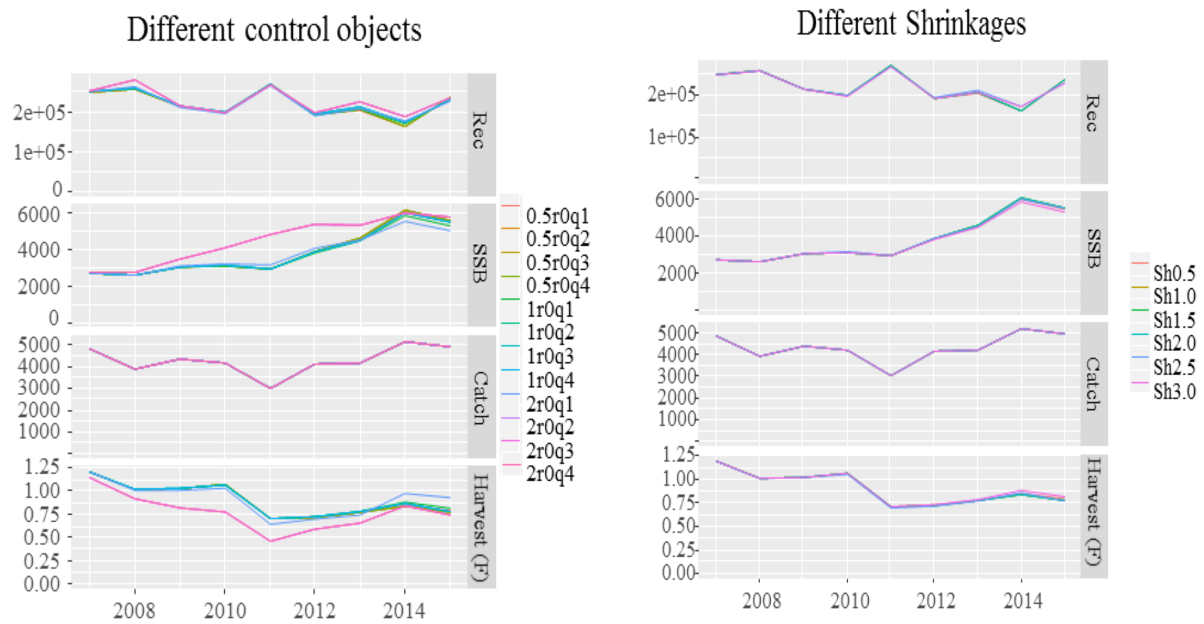


Figure 17 - European hake XSA control objects (Left-handed side) and XSA shrinkages (Right-handed side).

Shrinkage 1 provided the best results in fact, the residuals do not show any trend and were slightly lower. The best fitted model was the 1r0q3 and was chosen as final hake GSA 12-16 stock assessment. Recruitment, spawning stock biomass, catch and fishing mortality values as stock assessment outputs are presented in figure 18.

Recruitment in the stock is being constant/decreasing while spawning stock biomass has increased from 3000 tons in 2008 to 5533 tons in 2015. Fishing mortality has decreased from 1.25 to 0.81, having a negative peak in 2010. Catches have been slightly increasing during the timeseries.

XSA allowed to calculate the estimation of the spawning stock biomass (SSB) in addition to the total biomass (TSB). The period between 2007 to 2015 could be considered as a short period, although the ratio SSB/TSB shows annual variations between 50% for the target stock. The results revealed an increasing trend in the SSB along the years.

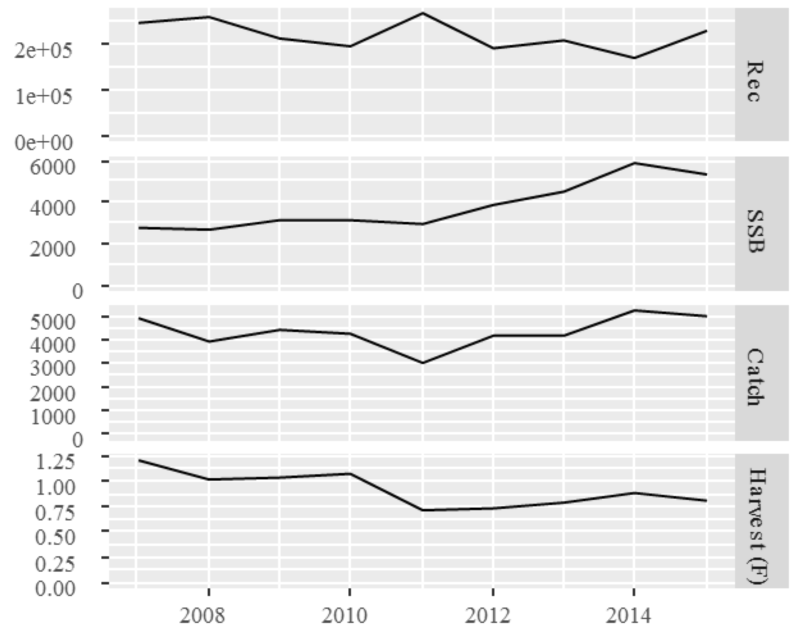


Figure 18 - European hake in GSA 12-16. Estimates of recruitment, SSB, Catch and F for the final run

3.1.1.1.- Diagnostics

The residuals show a decreasing trend but otherwise no pattern (Table 8).

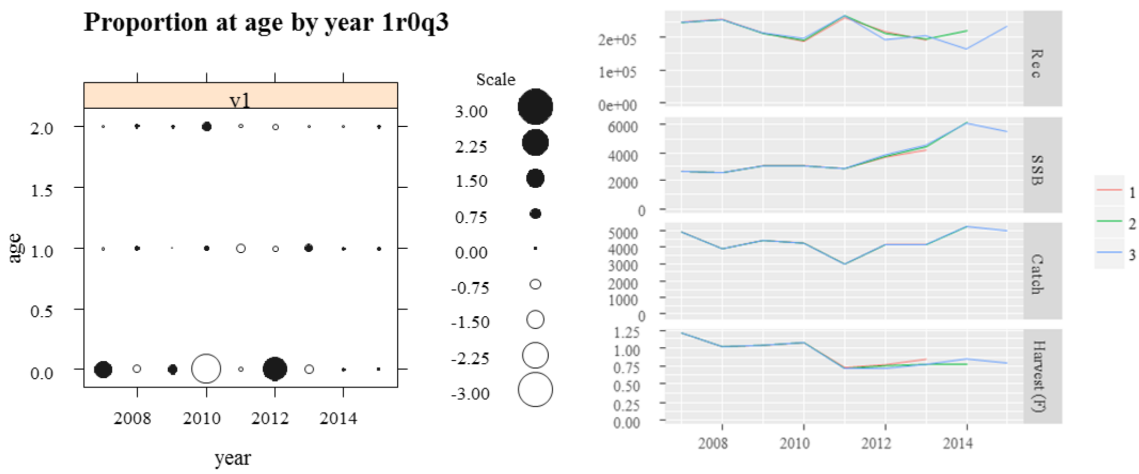


Figure 19 - European hake in GSA 12 -16. XSA. Diagnostics for the best run for shrk.age=1. Log Residuals of the best XSA configuration analysis (left), retrospective analysis (right).

Despite of all the diagnostic analysis were good in all the runs the 1r0q3 was slightly the best. Retrospective analysis shows good correlation between cohorts and consistent results. Residuals per age and year of the tuning fleet were relatively low, ranging from -3 to 3 and did not show any tendency with time (Table 8).

3.1.1.2.- Reference Points

The diagnostics of stock status shows; i) high overfishing and overexploited status ($F_{current} < F_{0.1}$), ii) relative low biomass.

Table 8 - European hake GSA 12-16 XSA reference points

$F_{current}$	0.81
F_{MSY}	0.180
$F_{0.1}$	0.117
$F_{current}/F_{0.1}$	6.92
F_{max}	0.180
Current SSB (tons)	5333.3
33rd percentile SSB (tons)	1759.9
66th percentile SSB (tons)	3519.9

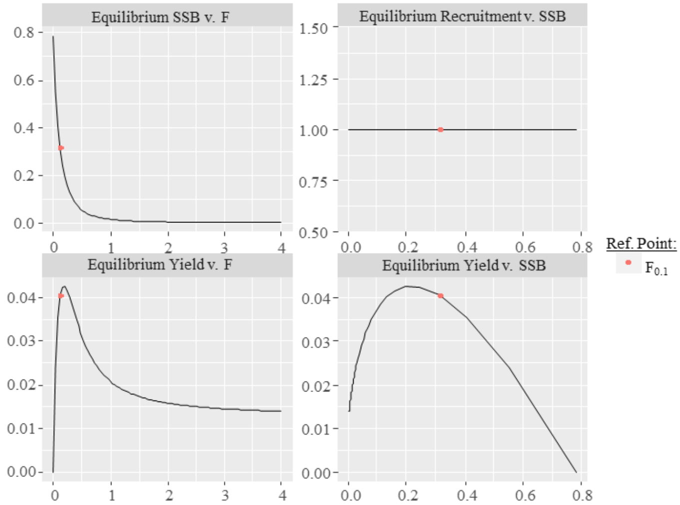


Figure 20 - European Hake GSA 12-16 Summary of the yield per recruit analysis (Y/R) results.

The results of the Y/R analysis (table 8, figure 20) showed that the present rate of exploitation (equal to 1) is beyond the optimal biological yield for sex combined European hake stock.

The reference points calculation shows $F_{current}$ (0.81) > $F_{0.1}$ (0.117). The ratio $F_{current}/F_{0.1}$ is 6.92. It means that the current stock status is overexploited. The survey data timeseries indicated a relative intermediate biomass of the stock. A reduction of approximately 592% is necessary to manage the resource to biological safe limits.

For that reason, as agreed with the WGSAD 2015, a reduction of fishing mortality towards the reference point is advised.

3.1.2.- Deterministic Assessment for All (a4a)

Deterministic a4a stock assessment results were similar to XSA. Due the introduction of a filter in the F, spawning stock biomass and fishing mortality models the results are softer. Main results are presented in figure 21. A4a assessment shows a variable but constant mean recruitment along the timeseries. SSB has been increasing since 2010 to 2014. It is possible to see a light decreasing in the trend during the last reported year. Catch has been increasing slightly during the time series. Fishing mortality values are variable during the timeseries.

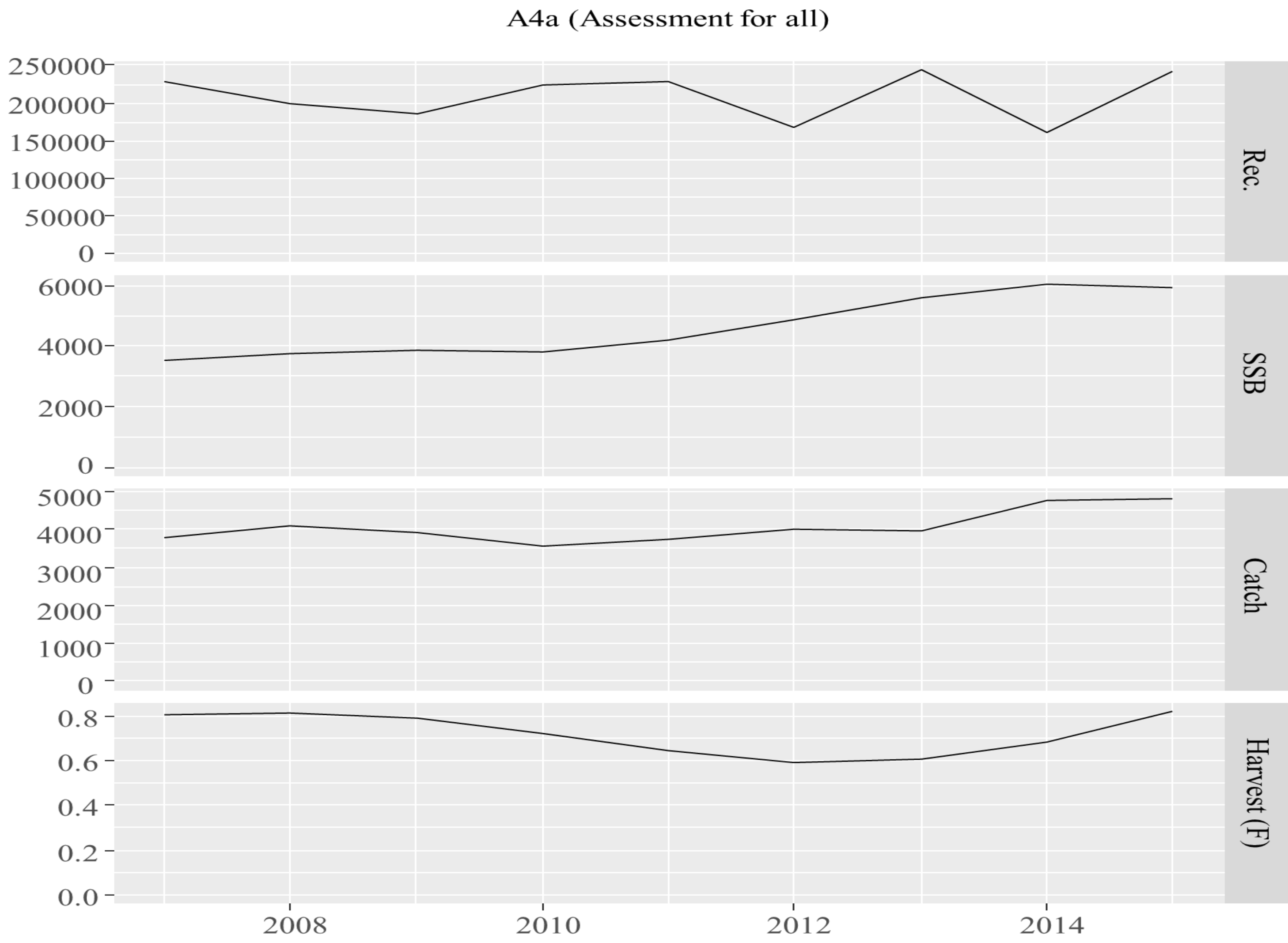


Figure 21 - European hake in GSA 12-16. Estimates of recruitment, SSB, Catch and F for deterministic a4a final run.

3.1.2.1.- Diagnostics

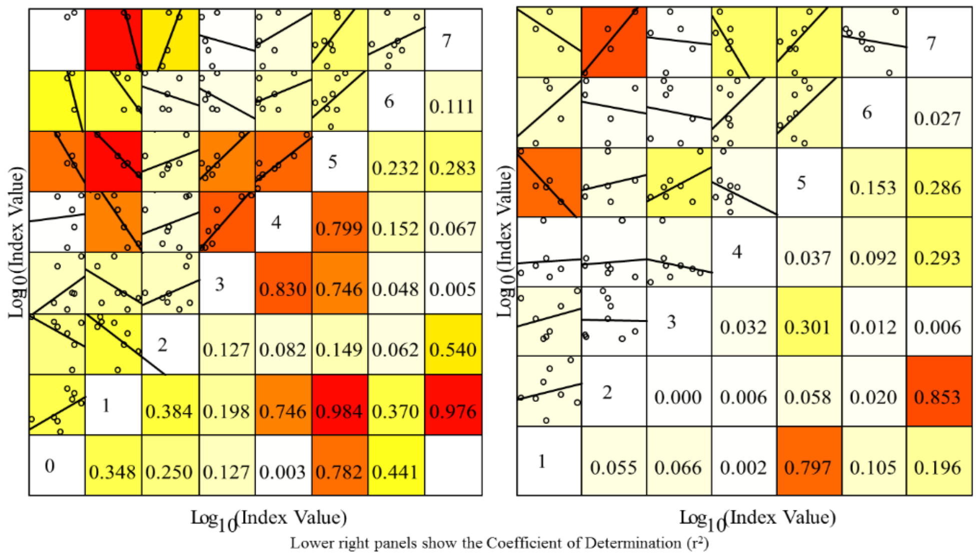


Figure 22 - European Hake GSA 12-16. Coefficient of determination diagnostics shows a problem in index related data values. Ages 0 and 1 presented problems in fitting.

We can plot fitted against observed catch numbers at age, where model fitted numbers are lines in light grey and observed is black line. The prediction is quite similar to the observed. It means that the catchability model, fishing mortality model and stock-recruitment model were well chosen to the stock assessment.

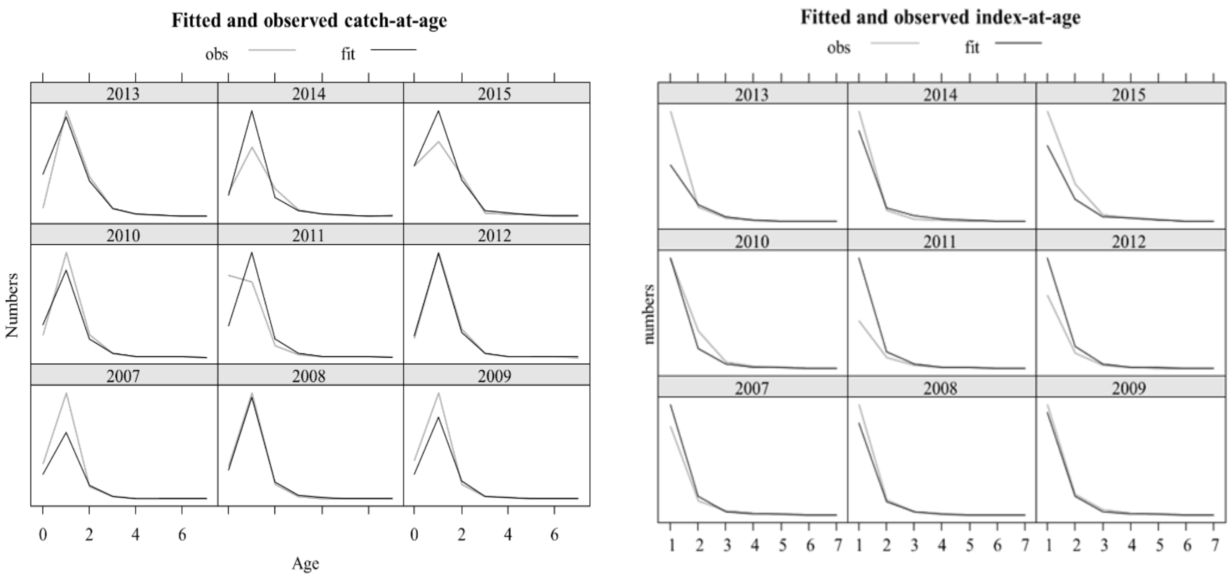


Figure 23 - European hake, GSA 12-16. Deterministic a4a diagnostics results.

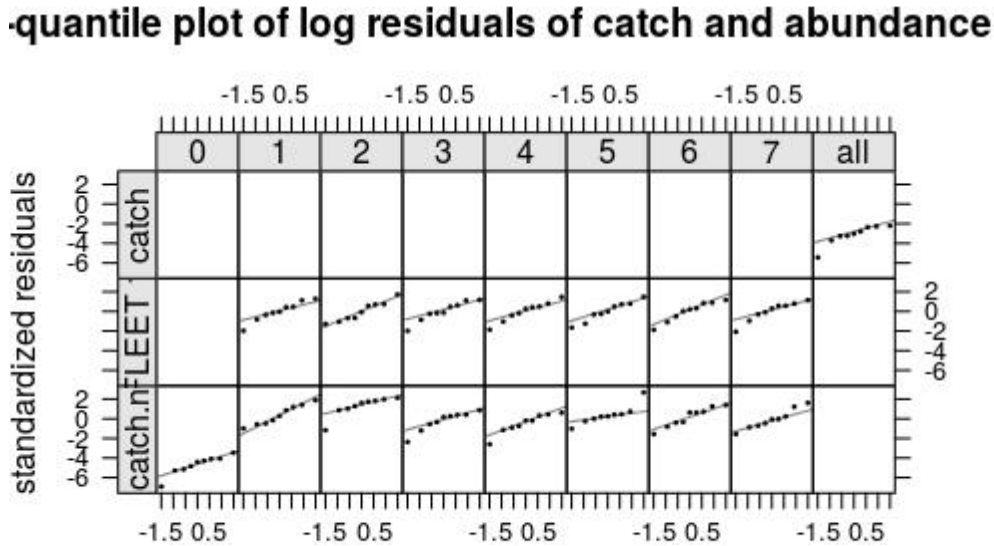


Figure 25 - Quantile plot of log residuals diagnostics shows a good fitting level in the stock assessment diagnostics.

Quantile plot shows a good residuals fitting, keeping the values between -2 and 2. There are not strong residuals trend in the survey for all ages.

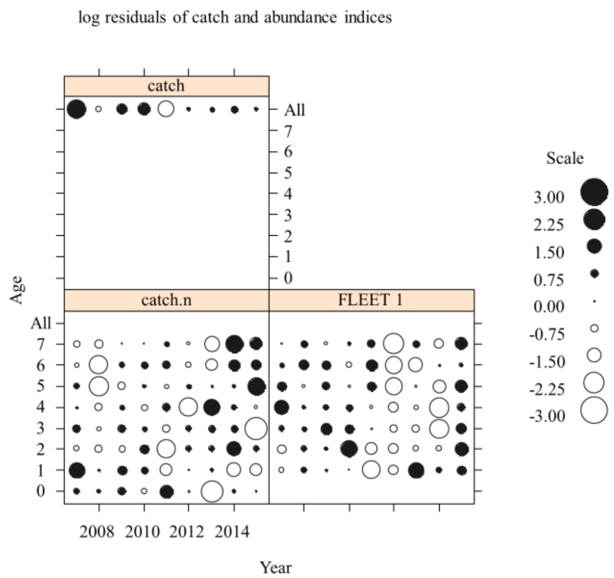


Figure 24 - European hake in GSA 12 -16. Bubble plot, Deterministic a4a assessment residuals.

3.1.2.2.- Reference Points

Reference points shows an overexploited stock status ($F_{current}/F_{0.1} = 4$) with relative high biomass. The fishing effort that could lead to the fishery towards biological safe limits is estimated in **¡Error! No se encuentra el origen de la referencia.**26. $F_{0.1}$ could be achieved w ith a reduction of 300% $F_{current}$. Biomass value is relatively high.

Table 9 - European hake GSA 12-16 Deterministic a4a reference points

$F_{current}$	0.70
F_{MSY}	0.180
$F_{0.1}$	0.117
$F_{current}/F_{0.1}$	5.98
F_{max}	0.274
Current SSB (tons)	8710.3
B_{lim}	2806.5
B_{pa}	3929.1

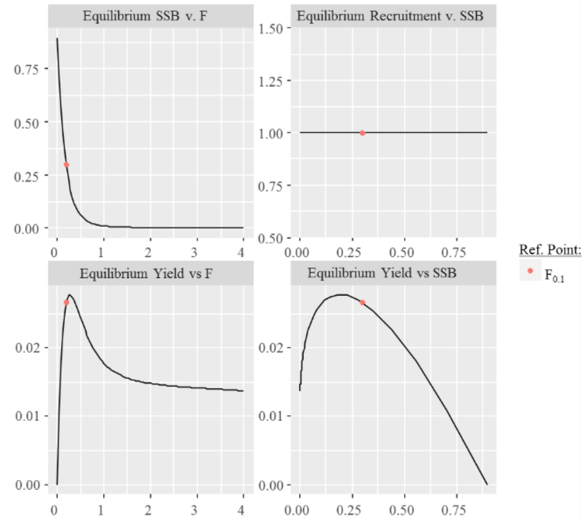


Figure 26 - European Hake GSA 12-16 Summary of the yield per recruit analysis (Y/R) results.

3.1.3.- Comparison a4a vs XSA

We compare the a4a model fit with the XSA fitted model. There are no significant differences between both models. Main differences are in SSB and F ratio. The trend is the same for both stock assessments.

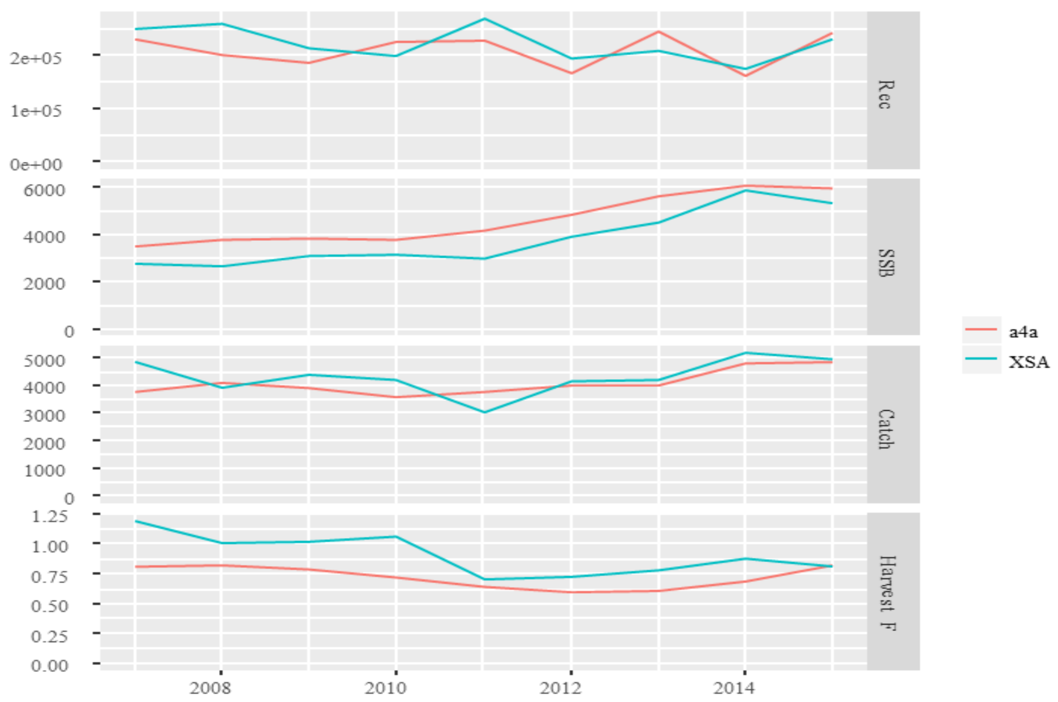


Figure 27 - European hake GSA 12 - 16. XSA and a4a results comparison.

3.1.4.- Stochastic Assessment for All (a4a)

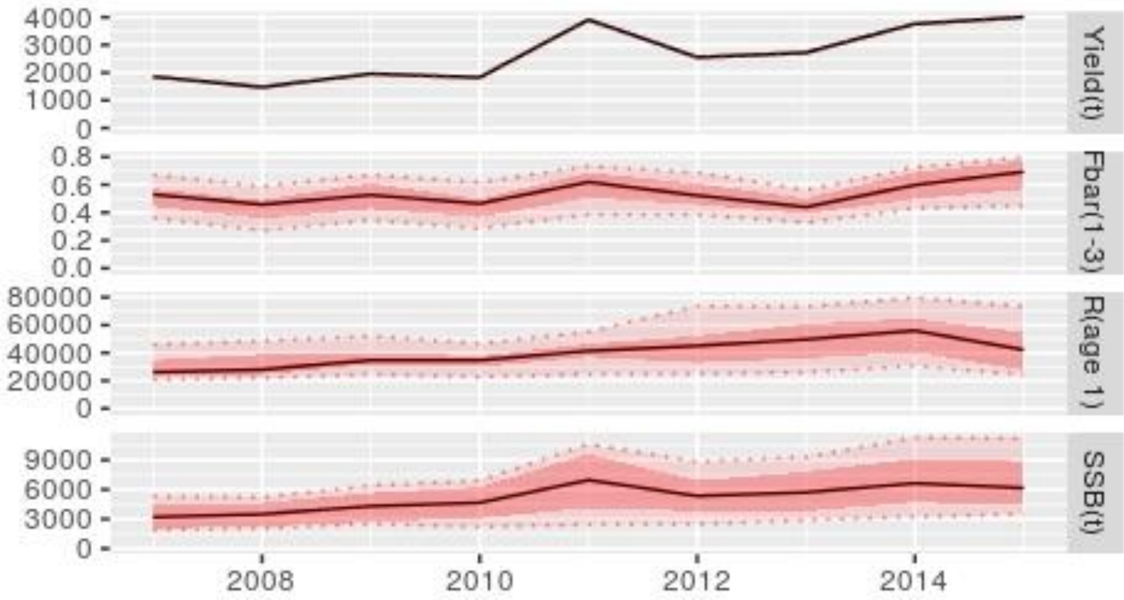


Figure 28 - European hake GSA 12-16. Stochastic a4a results.

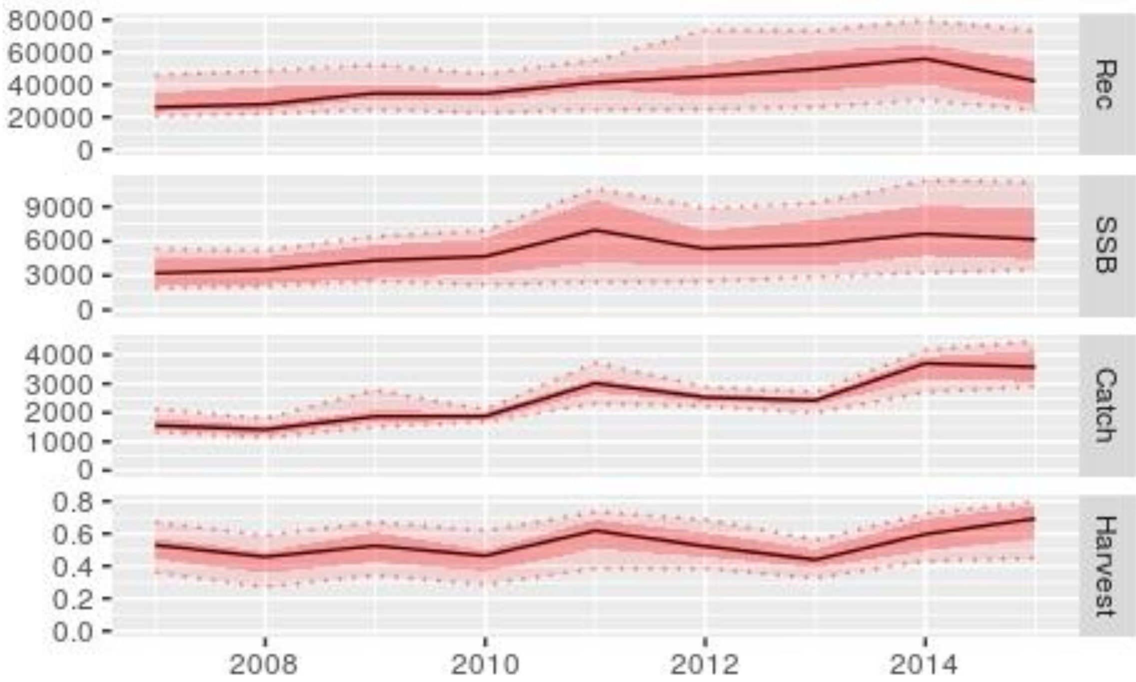


Figure 29 - European hake GSA 12-16. Stochastic a4a results.

In this stock assessment model, it is possible detect the appearance of limits and confidence intervals. Dark red lines mean the 33rd percentile and light red lines are the 66th percentile. Recruitment as in previous models keeps constant and no trend evolution during the years. SSB increases slightly along the timeseries. Catch increases along the years but are significantly lower comparing with the rest of models. Some data problems are reported in this section.

Figure 28 shows a yield increasing during the reported years. $F_{bar\ (1\text{-}3)}$ remained constant during the timeseries.

3.1.4.1.- Reference points

Reference points calculation detected overexploitation of the target stock ($F_{current}/F_{0.1}$ = 8 – 3.22). The 2 values are due the presence of confidence intervals. Biomass is relatively high.

Table 10 - European hake GSA 12-16 Stochastic a4a reference points

$F_{current}$	0.69246 ± 0.1182
F_{MSY}	0.21307 ± 0.0643
$F_{0.1}$	0.14407 ± 0.0450
$F_{current}/F_{0.1}$	8 – 3.22
F_{max}	0.21307 ± 0.0643
Current SSB (tons)	4845.4 ± 1448
B_{lim}	1598.8
B_{pa}	3197.96

3.2.- Short term forecast

3.2.1.- XSA

Table 11 - European Hake in GSA 12-16. XSA. Short term forecast under different F scenarios (3-year average, 2013-2015) weight at age, maturity at age and F at age. Recruitment (age 0) geomean 2013-2015.

	Ffactor	Fbar	Catch 2015	Catch 2016	Catch 2017	Catch 2018	SSB 2017	SSB 2018	Change SSB 2017-2018(%)	Change Catch 2015-2016(%)
1	0.00	0.00	4959.23	4869.48	0.00	0.00	5089.42	10749.32	111.21	-100.00
2	0.10	0.08	4959.23	4869.48	689.68	1206.67	5089.42	9845.40	93.45	-86.09
3	0.20	0.17	4959.23	4869.48	1322.02	2155.06	5089.42	9025.54	77.34	-73.34
4	0.30	0.25	4959.23	4869.48	1902.27	2893.16	5089.42	8281.53	62.72	-61.64
5	0.40	0.33	4959.23	4869.48	2435.15	3460.47	5089.42	7606.00	49.45	-50.90
6	0.50	0.41	4959.23	4869.48	2924.94	3889.47	5089.42	6992.32	37.39	-41.02
7	0.60	0.50	4959.23	4869.48	3375.50	4206.82	5089.42	6434.53	26.43	-31.94
8	0.70	0.58	4959.23	4869.48	3790.32	4434.42	5089.42	5927.28	16.46	-23.57
9	0.80	0.66	4959.23	4869.48	4172.58	4590.18	5089.42	5465.72	7.39	-15.86
10	0.90	0.75	4959.23	4869.48	4525.12	4688.78	5089.42	5045.52	-0.86	-8.75
11	1.00	0.83	4959.23	4869.48	4850.56	4742.19	5089.42	4662.76	-8.38	-2.19
12	1.10	0.91	4959.23	4869.48	5151.23	4760.19	5089.42	4313.92	-15.24	3.87
13	1.20	0.99	4959.23	4869.48	5429.28	4750.72	5089.42	3995.80	-21.49	9.48
14	1.30	1.08	4959.23	4869.48	5686.64	4720.21	5089.42	3705.55	-27.19	14.67
15	1.40	1.16	4959.23	4869.48	5925.06	4673.88	5089.42	3440.58	-32.40	19.48
16	1.50	1.24	4959.23	4869.48	6146.15	4615.93	5089.42	3198.54	-37.15	23.93
17	1.60	1.33	4959.23	4869.48	6351.36	4549.72	5089.42	2977.32	-41.50	28.07
18	1.70	1.41	4959.23	4869.48	6542.00	4477.95	5089.42	2775.03	-45.47	31.92
19	1.80	1.49	4959.23	4869.48	6719.29	4402.75	5089.42	2589.93	-49.11	35.49
20	1.90	1.57	4959.23	4869.48	6884.30	4325.80	5089.42	2420.47	-52.44	38.82
21	2.00	1.66	4959.23	4869.48	7038.05	4248.41	5089.42	2265.23	-55.49	41.92
22	0.22	0.18	4959.23	4869.48	1426.11	2296.75	5089.42	8891.46	74.70	-71.24

Short term projection shows that: i) Fishing a at $F_{status\ quo}$ (0.81) generates a decreasing of the catch of approximately 23% from 2017 to 2018 along with an increasing of the spawning stock biomass of the 16% from 2017 to 2018; ii) fishing at $F_{0.1}$ (0.22) generates a decrease of the catch of the 71% from 2017 to 2018 and an increase of the spawning stock biomass of 74% from 2017 to 2018.

Different and alternative scenarios are shown at Table 12.

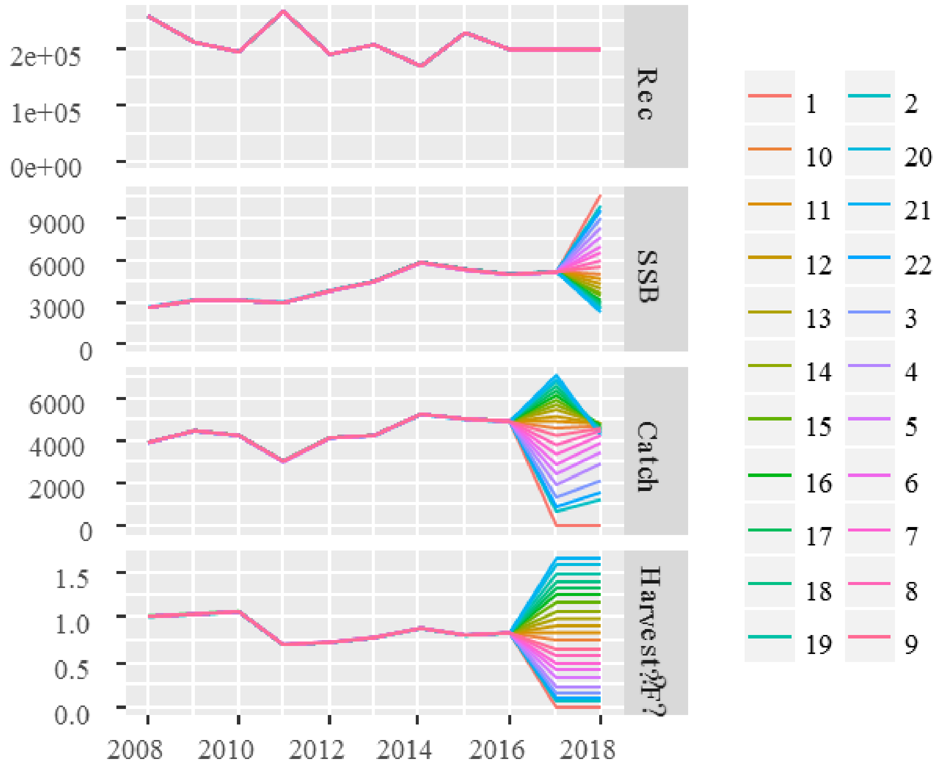


Figure 30 - XSA short term forecast.

3.2.2.- Deterministic a4a

Deterministic a4a short-term forecasting demonstrate the similarity in the results between both models. Fishing at $F_{status\ quo}$ level will generate a change in the SSB of 9%. Catches could increase 26% of the total catch value since 2015 – 2016. Fishing at F0.1 level could increase the SSB up to 52%, and catches could be reduced 55%.

Different and alternative scenarios are at Table 12.

Table 12 - European Hake in GSA 12-16. Deterministic a4a short term forecast under different F scenarios (3-year average, 2013-2015) weight at age, maturity at age and F at age. Recruitment (age 0) geomean 2013-2015

	Ffactor	F_{bar}	Catch 2015	Catch 2016	Catch 2017	Catch 2018	SSB 2017	SSB 2018	Change SSB 2017-2018(%)	Change Catch 2015-2016(%)
1	0	0.00	5144.41	6164.13	0.00	0.00	12081.83	21388.62	77.03	-100.00
2	0.1	0.05	5144.41	6164.13	806.80	1207.56	12081.83	20354.36	68.47	-84.32
3	0.2	0.09	5144.41	6164.13	1574.12	2254.61	12081.83	19377.28	60.38	-69.40
4	0.3	0.14	5144.41	6164.13	2304.15	3160.35	12081.83	18453.97	52.74	-55.21
5	0.4	0.18	5144.41	6164.13	2998.94	3941.73	12081.83	17581.26	45.52	-41.70
6	0.5	0.23	5144.41	6164.13	3660.43	4613.70	12081.83	16756.16	38.69	-28.85
7	0.6	0.28	5144.41	6164.13	4290.45	5189.45	12081.83	15975.87	32.23	-16.60
8	0.7	0.32	5144.41	6164.13	4890.70	5680.59	12081.83	15237.76	26.12	-4.93
9	0.8	0.37	5144.41	6164.13	5462.79	6097.40	12081.83	14539.36	20.34	6.19
10	0.9	0.41	5144.41	6164.13	6008.26	6448.93	12081.83	13878.36	14.87	16.79
11	1	0.46	5144.41	6164.13	6528.52	6743.16	12081.83	13252.57	9.69	26.90
12	1.1	0.51	5144.41	6164.13	7024.91	6987.15	12081.83	12659.96	4.79	36.55
13	1.2	0.55	5144.41	6164.13	7498.72	7187.11	12081.83	12098.62	0.14	45.76
14	1.3	0.60	5144.41	6164.13	7951.14	7348.53	12081.83	11566.73	-4.26	54.56
15	1.4	0.64	5144.41	6164.13	8383.28	7476.24	12081.83	11062.61	-8.44	62.96
16	1.5	0.69	5144.41	6164.13	8796.21	7574.52	12081.83	10584.67	-12.39	70.99
17	1.6	0.74	5144.41	6164.13	9190.94	7647.13	12081.83	10131.42	-16.14	78.66
18	1.7	0.78	5144.41	6164.13	9568.40	7697.40	12081.83	9701.46	-19.70	86.00
19	1.8	0.83	5144.41	6164.13	9929.48	7728.24	12081.83	9293.45	-23.08	93.01
20	1.9	0.87	5144.41	6164.13	10275.02	7742.25	12081.83	8906.18	-26.28	99.73
21	2	0.92	5144.41	6164.13	10605.82	7741.69	12081.83	8538.47	-29.33	106.16
22	0.29	0.14	5144.41	6164.13	2293.20	3147.41	12081.83	18467.77	52.86	-55.42

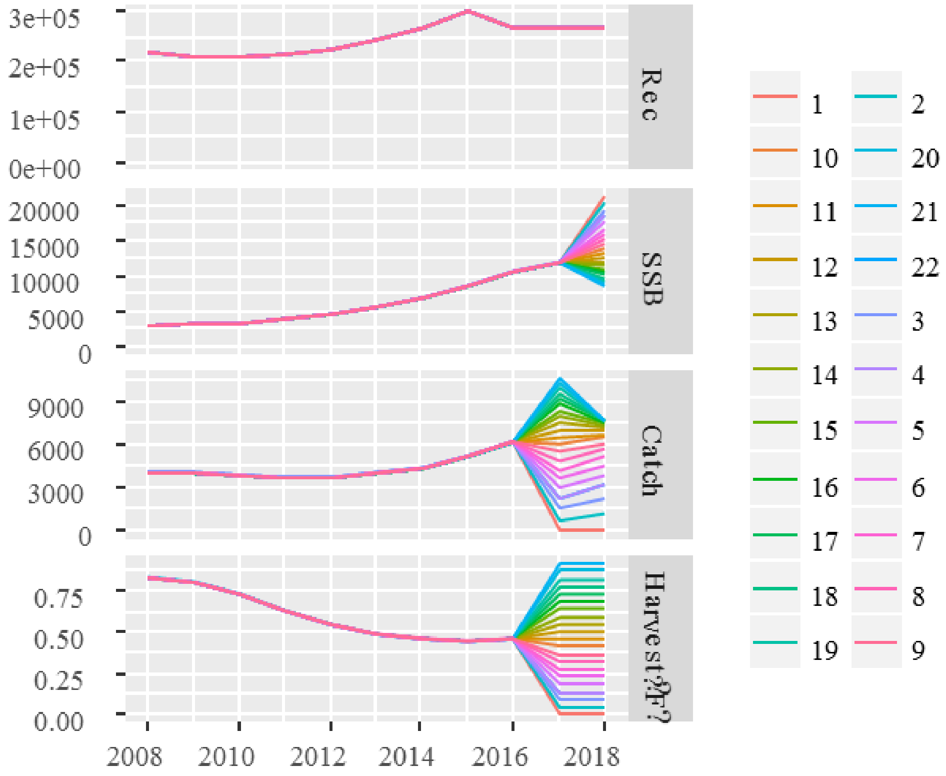


Figure 31 - Deterministic a4a short term forecast

3.3.- Medium-Long term forecast and assessment of management scenarios

3.3.1.- XSA

Management strategy evaluation for extended survivor analysis stock assessment has shown that in Status Quo scenario no significant change in stock status happened. Recruitment, spawning stock biomass, catch and fishing mortality remained constant during projected years. The possibility of dropping below B_{lim} was equal to 0.

During the achievement of $F_{0.1}$reference point choosing $F_{0.1}$ as a proxy of Fmsy showed a high and fast increasing of the spawning stock biomass, generating proportional increasing of the catch values along the projected years. Recruitment remained constant and fishing mortality also at $F_{0.1}$ level (0.22). The possibility of dropping below B_{lim} was equal to 0.

In the reduction of 50% of current F, the simulations generated an increasing of the spawning stock biomass and catch. Recruitment was constant and F at level of 0.4 too. This measure generates an important stock recovery effect. The possibility of dropping below B_{lim} was equal to 0.

Increasing the previous scenario to a 70% F reduction, the stock recovery capacity was increased comparing with the previous scenario. The recovery time (slope of the graph) and maximum level of SSB increased significantly. The possibility of dropping below B_{lim} was equal to 0.

Most restrictive scenario (90% F reduction) generated the expected effect. Fast increase and maximum level of the SSB during time series was noticed. Recruitment, as in the previous scenarios remained constant. The possibility of dropping below B_{lim} wa equal to 0.

3.3.2.- Deterministic a4a

Assessing Status Quo scenario, recruitment, spawning stock biomass, catches and fishing mortality remained constant during all projected years. No significant changes took place in the stock status. The possibility of dropping below B_{lim} is equal to 0.

During $F_{0.1}$ scenario, recruitment remained constant and harvest decreased until $F_{0.1}$ level and kept constant during the timeseries (from 2016 to 2035 F is equal to 0.11). In the scenario, there were significant changes in the SSB and in catches. Both variables increased significantly. The possibility of dropping below Blim is equal to 0.

50% F reduction scenario showed that recruitment was kept constant while SSB and catches increased significantly with the same slope for both variables. There was no possibility of dropping below B_{lim}.

70% F reduction, as in the previous model, recruitment remained constant and the rest of variables (excepting fishing mortality) increased to 10000 tons and 6000 tons for spawning stock biomass and catches respectively. The possibility of dropping below Blim was equal to 0.

In 90% F reduction scenario changes were more significant, spawning stock biomass increased to 100000 tons and catches to 7500 tons. Recruitment, as in the previous scenarios remained constant. No possibility of dropping below B_{lim} existed in this scenario.

3.3.3.- Stochastic a4a

Management strategy evaluation showed higher uncertainty boundaries in forecasting.

During scenario 1, Status Quo, no significant changes occurred in stock values. SSB decreased non-significantly. Catch value remained constant along the timeseries. No significant variations took place in this scenario. There existed a possibility of dropping below Blim in this scenario.

In $F_{0.1}$ scenario, F decreased until the $F_{0.1}$ value. Catches, after a big peak, increased significantly. Also spawning stock biomass increased overcoming historical maximums. As in the rest of scenarios, recruitment remained constant. No possibility of dropping below B_{lim} existed in this scenario.

50% F reduction scenario showed a decrease in catches significantly until 2020, when catches slightly increased. A high reduction on fishing mortality took place arriving to historical minimums. A low increase in spawning stock biomass happened in this scenario. No possibility of dropping below B_{lim} existed in this scenario.

Along 70% F reduction SSB was increased. Catch, after a low peak was recovered bellow historical minimum. As in the rest of scenarios, recruitment remained constant. The possibility of dropping below B_{lim} in this scenario existed.

During 90% F reduction scenario, the spawning stock biomass increased significantly. Catches are approximately 30% of the historical value and F remained in historical minimums. Recruitment still constant. Low possibility of dropping below B_{lim} exists.

XSA Long Term Forecast

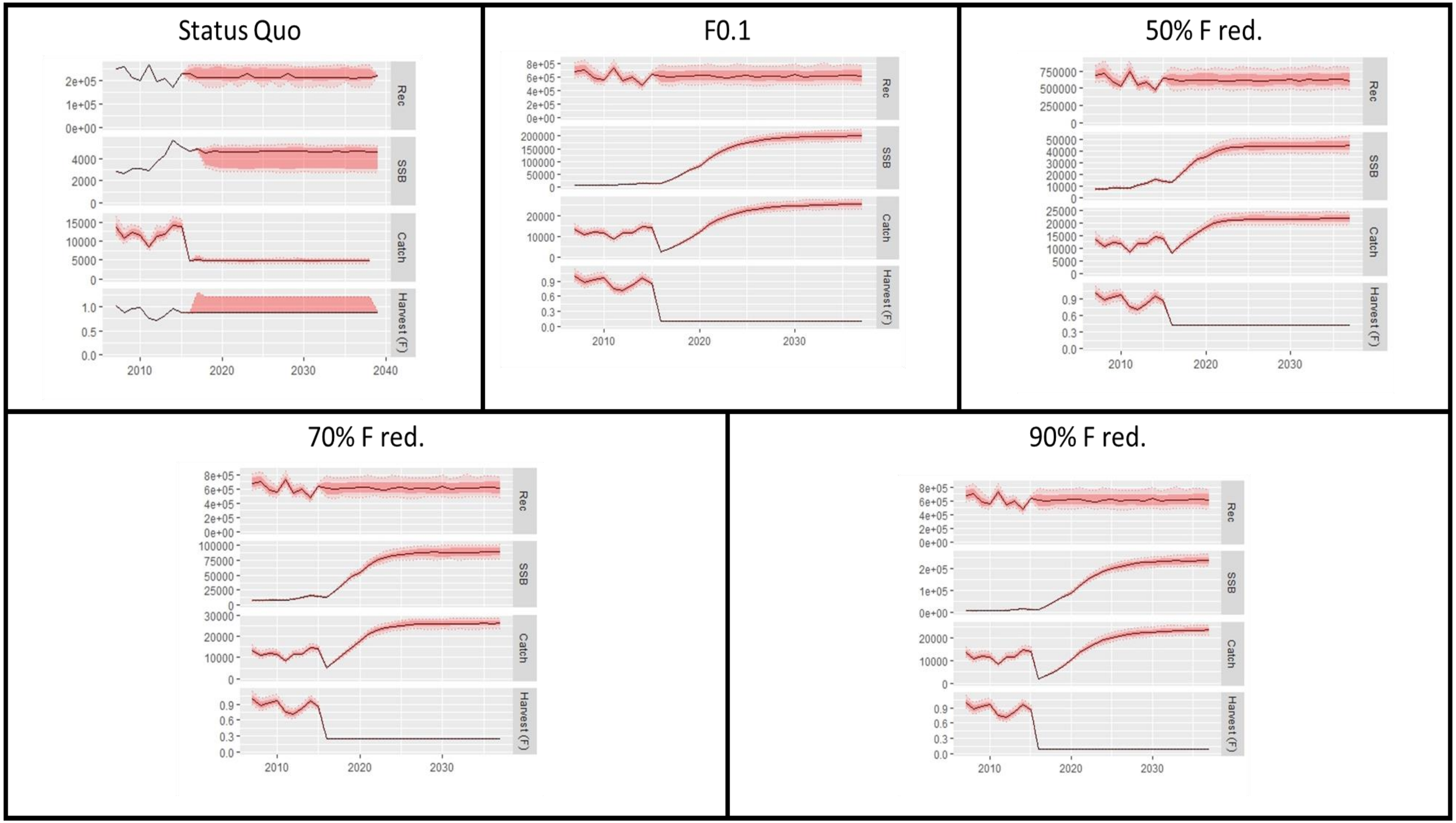


Figure 32 - XSA Forecasting and assessment of management scenarios.

Deterministic a4a Long Term Forecast

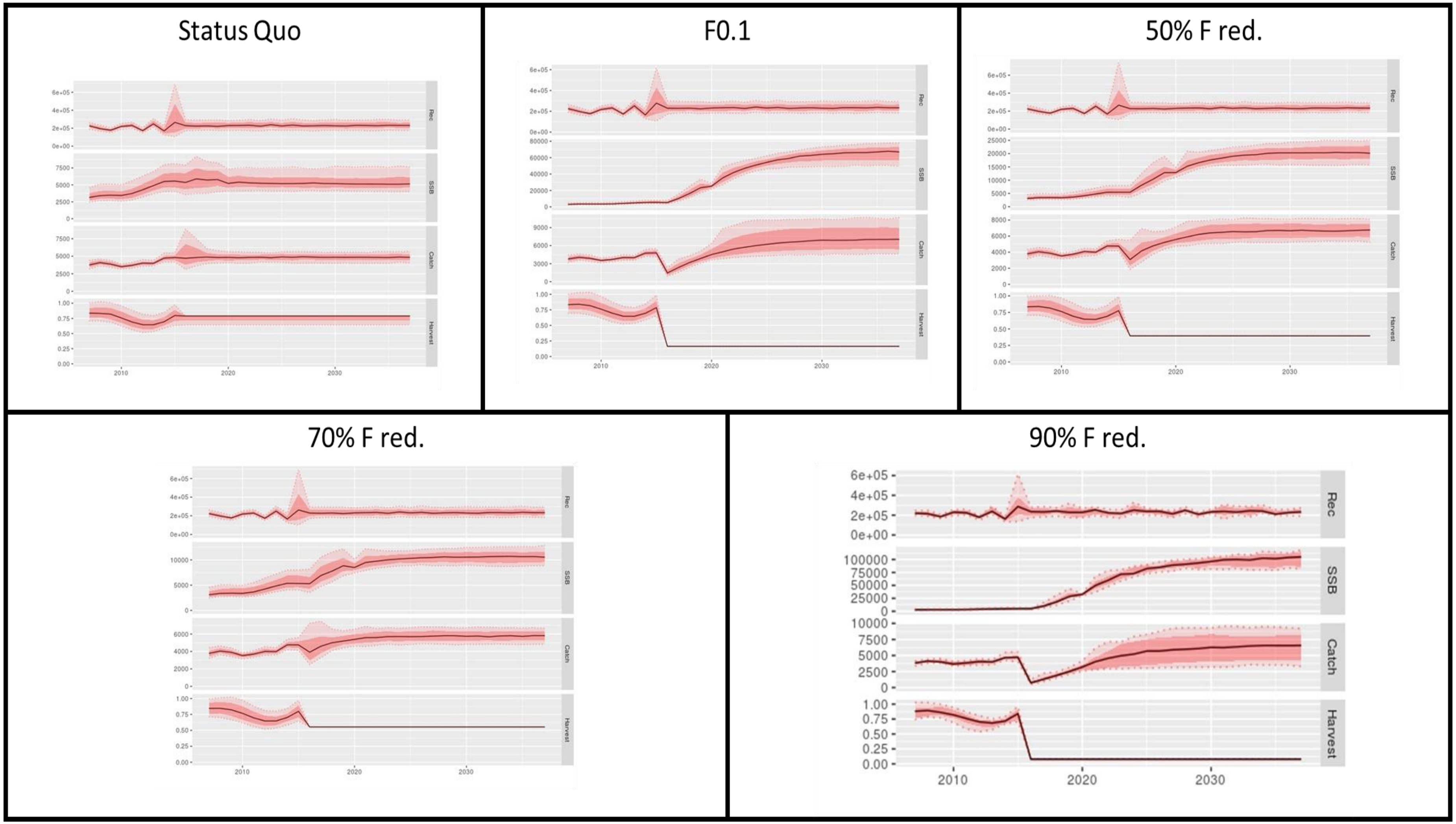


Figure 33 - Deterministic a4a forecasting and assessment of management scenarios.

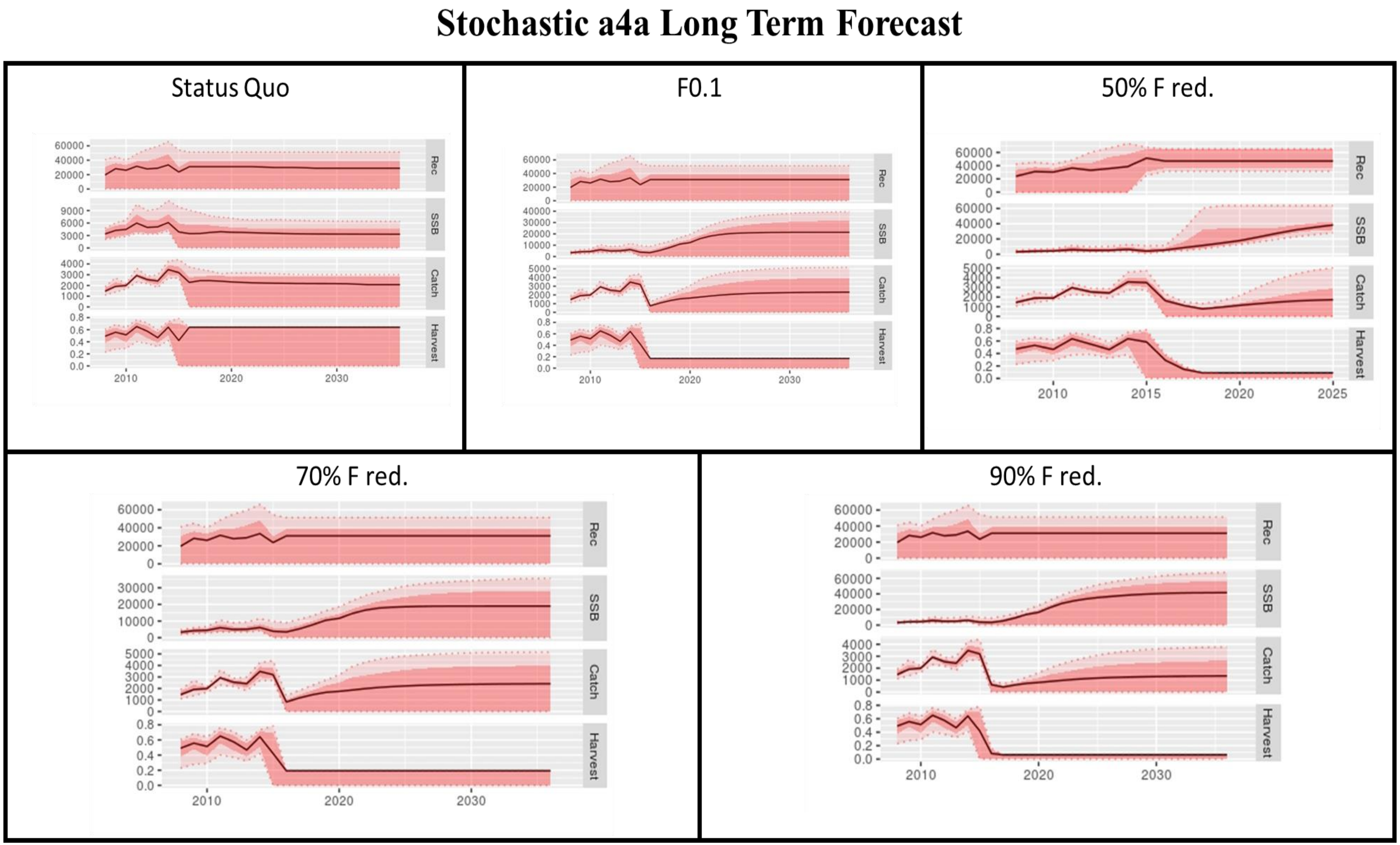


Figure 34 - Stochastic a4a forecasting and assessment of management scenarios.

4.- Discussion

4.1.- Stock assessment results and advice

As during the 2016 working group on stock assessment (GFCM WGSAD, 2016), XSA European hake stock assessment showed an overexploited status of the resource ($F_{curr} > F_{0.1}$) with a relative intermediate biomass in GSAs 12 -16. Despite of diagnosis of the stock status is the same for the three models used during the research (XSA, deterministic a4a and stochastic a4a), the values of F_{curr} and $SSB_{curr.}$ are quite different. The reason to explain the differences in some stock assessment outputs could be the differences between how each model computes catchability and the way to estimate the biomass. XSA has problems to incorporate selectivity patterns and uncatchable individuals for the fishing gear due accessibility. a4a estimates the individuals impossible to catch by the fishing gear. The reference points estimated by all models were similar with slight differences.

In developed stock assessment achieving $F_{0.1}$ implies a reduction in current fishing mortality of 80, 70 and 65 percent in XSA, deterministic a4a and stochastic a4a respectively. European hake in GSAs 12-16 is a shared stock by Italy, Malta and Tunisia. For that reason, F_{curr} should be reduced considering the contribution to the catch of each fleet exploiting the stock.

Concerning to the used models, XSA and a4a are methods based on pseudocohorts analysis. Those methods assume of the equilibrium of the stocks and its exploitation and the constancy of the annual recruitment (Aldebert & Recasens 1996). Historically, along the studied timeseries, the conditions of the exploitation of hake stock in GSAs 12 – 16 remained quite steady (Fiorentino *et al.*, 2003). However, constant recruitment trend has been observed without peaks along the timeseries but with important large landings of group 0 fish. Pseudocohorts based on 8 years and constant recruitment trend are enough to obtain robust results. Some of the Extended Survival Analysis limitations are: i) Stochasticity in the model for a proper description of the stocks; ii) Incapability to separate the effects of different fleets and therefore simulate the effects of different management measures on different fleets; iii) Impossibility to incorporate spatial aspects when assessing management scenarios; iv) Impossibility to incorporate species interactions, as well as interactions with the environment; v) Impossible to deal with bioeconomical information to test potential effects of alternative management scenarios on the fishery.

Through the calculation of stock assessment diagnostics, some problems in some ages and during some years were noticed. Specially in the catch-at-age matrix. Age 0 probably is not well represented. The possible cause are the difficulties to sample discards in the Mediterranean and Black sea fisheries. It makes difficult to simulate the effects of an improvement in selectivity and other management scenarios. Also, the data series used to do the stock assessment are enough, but ideally, more years are necessary to improve the stock assessement quality. Also, relating to growth and natural mortality parameters, there are existing gaps on the calculation of those parameters. It is necessary continue with data acquisition inside “GFCM data collection reference framework” to increase the data acquisition, data quality and obtain better timeseries. GFCM data collection reference framework “is the first comprehensive GFCM framework for the collection and submission of fisheries-related data in the GFCM area (Mediterranean and Black Sea). It is the result of a series of coordinated actions focused on fisheries data collection which were launched in 2013 under the umbrella of GFCM Scientific Advisory Committee (SAC) and considering the inputs of the GFCM Working Group on the Black Sea (WGBS) (GFCM DCRF, 2016)". This tool indicates how to obtain different kind of data. Some of the referred data are: i) National fisheries; ii) Catch; iii) Incidental catch of vulnerable species; iv) Fleet; v) Effort; vi) Socioeconomics; vii) Biological information. It also indicates the "common practices in data collection". These data are of paramount importance for the work of the GFCM to support to the decision-making process based on sound scientific advice from its subsidiary bodies (GFCM DCRF, 2016). As agreed with GFCM WGSAD, it is recommended to stablish a European hake tagging project to obtain essential data on growth, natural mortality, migration patterns and connectivity.

4.2.- Uncertainty in Stock Assessment: Stochastic a4a

Measurement (observation) uncertainty occurs in any process of collecting field data, and might be due to crude devices or mistakes during measurement. These two forms of uncertainty combine to form parameter uncertainty. Structural uncertainty (also called 'model uncertainty') has received increased attention in modelling natural resources and represents our lack of understanding of the dynamics of the system. Representing structural uncertainty is generally difficult because a model representing the real system according to our perceptions is only one possible way in which the system could function. Implementation uncertainty surrounds the translation of policy into practice, and has been poorly covered in the literature on natural resources because its causes lie within social science; one example is institutional inertia, another is non-compliance with rules. MSE models the entire resource management system rather than just the resource stock dynamics. Hence, it can incorporate all these types of uncertainty and quantify their relative importance (Bunnefeld *et al.,* 2011).

Stochastic assessment for all seems the best alternative to replace extended survival analysis during the stock assessment process. This work agrees with the WGSAD (GFCM WGSAD, 2016) and demonstrates that statistical-catch-at-age (SCAA) methods as a4a allowed to a better understanding of the fluctuations and dynamics of the stocks over the years. Those methods should be promoted in the assessment and management bodies in the Mediterranean region. Nevertheless, there are technical difficulties in shifting towards the use of such complex models. It is necessary increase capacity-building initiatives as, for example, trainings (GFCM WGSAD, 2016). However, during the realization of the research, we notified that a4a is an easier to use tool and to understand by the scientific non-specialized community in stock assessment.

Although uncertainty could be introduced in other ways using the same stock assessment model (for example, Markov Chain Monte Carlo simulation, bootstrapping, etc) (Ralston et al. 2011) those just represent the structural uncertainty[1]. Current investigation proposes include regularly other existing errors during the stock assessment process. As, for example, uncertainty in growth parameters or in natural mortality parameters. The aim would be obtaining better and more precise representations of the system reality in which ones' uncertainty had been considered. Other authors as Deroba

[1] Probability of the occurrence of an unanticipated event due to the configuration of a system.

et al., 2015 and Williams, 1997 proposed the same to increase the quality of the advice. Main problem of the deterministic approach (just one value without uncertainty) is that sometimes, the manager, to carry on the management measure it is built over the best simulation scenario (Deroba *et al.,* 2015) and not in extreme situations.

Nowadays, statistical-catch-at-age models as a4a or SAM and integrated analysis like SS3 or GADGET could allow us to estimate of reliable biomass reference points in stocks with robust stock-recruitment relationship estimations (GFCM WGSAD, 2016).

Those biomass reference points are key actors for the establishment of a harvest control rule (HCR). Harvest strategies and decision rules provide a formal and more consistent approach to the management decision making process by defining what actions will occur based on the current or likely future performance of a fishery in relation to one or more of its operational objectives (FAO - EAFnet). The establishment of HCR will help to develop political decisions to explicitly reflect long-term preferences (Kvamsdal, *et al.,* 2016) and definitively to better management of the resource.

4.3.- Assessment of Management Scenarios

Management processes (management strategy evaluation) is done to test and recommend management measures and assessment methods which take care about structural uncertainty and observed parameters during data collection process. Bioeconomical assessment should be done for the realization of a full MSE. For this reason, during the current investigation an assessment of management scenarios was done, not a full management strategy evaluation.

Within fisheries assessment and management, the MSE approach is the most closely related to the development and evaluation of management procedures. The key ingredients to develop a MSE are: i) Specifying key management objectives; ii) develop quantifiable performance measures for each objective; iii) identify alternative management strategies or decision options; iv) evaluate the performance of each strategy; v) communicate the results to decision makers (Smith *et al.,* 1999). Due the absence of time during the research, some of those parts were not assessed. It is the cause why a full MSE approach was not completed.

The management simulations depend on the stock assessment models adopted and are therefore subject to the same limitations and uncertainties as these models. Stock assessment uncertainties were in general well described by the WGSAs, which formulate recommendations every year to improve the quality of the stock assessment models. The quality of the input data and the duration of the time series were crucial for the analysis being necessary an extra effort to improve the information used in stock assessement and therefore ensure the best quality advice.

MSE, in common with adaptive management more generally, has four major advantages over standard approaches to providing management advice. Firstly, it allows experimentation with a range of possible management procedures under a range of circumstances. Real-world experimentation is highly desirable to disentangle the drivers of a system, but is difficult to pursue for most natural resources because of the dependence of individuals and firms on resources for their livelihoods and the spatial extent of the systems. In conservation, real-world experimentation poses ethical dilemmas: local people often depend on ecosystem services for subsistence, whereas endangered species may face extinction. Secondly, stakeholders can be directly involved in the development of the management scenarios and the evaluation of the metrics by which the performance of different management options is assessed. A key feature of the MSE approach is that an optimal strategy or solution is not pursued, but instead policies are sought that are feasible, robust to uncertainty, and which provide adequate management performance with respect to multiple criteria. This allows for more transparency in the management process and promotes the acceptance and support of stakeholders. Thirdly, MSE enables researchers and managers to examine the implications of various forms of uncertainty (including process, measurement and structural uncertainty) on the performance of different management options. Fourthly, MSE carries out prospective (rather than retrospective) evaluations of the performance of different management procedures under a range of circumstances. By comparing the performance of a range of alternative strategies under plausible scenarios upfront, the response of the system can be compared with the desired goals and evaluated in advance of implementation.

Limitations of MSE Management of natural resources is plagued by uncertainty and feedbacks between the dynamics of resources and users. Although MSE goes some way towards addressing these difficulties, it has been criticized for: (i) having a longer development time (and thus increased costs) than traditional methods such as reference-based off-take rules; (ii) an upfront MSE can provide an overly rigid framework without room for decision-makers to change management in an adaptive way; and (iii) poor data inputs (e.g., gaps in monitoring or extremely low estimates of uncertainty) affect the performance of MSE, which needs to be recognized and explored within the MSE process. These criticisms point to the need for an iterative process of monitoring, learning and adaptation, which is entirely in keeping with the MSE approach if practitioners are prepared to engage with the issues being raised.

Along the investigation, bioeconomic analysis were not performed except for an evaluation of variations in catch levels in response to the implementation of different management scenarios. It could be a continuation of the present work evaluating and assessing the bioeconomical implications of the proposed management scenarios. MEFISTO could be the tool to accomplish the objective.

4.4.- Mediterranean Sea: Status and future

Overall current situation of the Mediterranean stocks is bad (85% of overexploited stocks) (GFCM, 2016). However, there are indicators that countries are about the urgency of taking measures and actions to improve the quality of advice and the management of stocks. For example, i) the percentage of assessed landings has nearly doubled in recent years, rising from 20 percent in 2013 to 45 percent in 2015 (GFCM, 2016). It is a good reference point to assess the improvement of the scientific advice.

Also, there are important initiatives on way that could be good guidelines to progress and improve the scientific advice. Some initiatives, in addition of GFCM Mid-Term strategy, for the Mediterranean Sea are: i) The use of fleet-based assessment models as operational models for the assessment of management scenarios towards a more comprehensive Management Strategy Evaluation (MSE) framework including uncertainty and evaluation of socioeconomic impact (GFCM, SAC, 2016); ii) The improvement of stock biological information; iii) The creation of a management plan for small pelagic fisheries management in Adriatic Sea; iv) The increase of the technical and operational measures to facilitate the provision of advice for the GFCM; v) The creation of areas of discussion at subregional level to create discussions and deliberations on fisheries management in their subregion and vi) The development of training courses.

Within this context the improvement on coverage and the precision of the advice should facilitate the adoption of more and better management measures to improve the state of Mediterranean and Black Sea fisheries.

5.- Conclusion

The obtained results during this master thesis are consistent with previous scientific advice given to the Central Mediterranean subregion for European hake.

- European hake in GSA 12-16 stock assessment has shown an overexploited status of the resource being necessary the adoption of measures to reduce the fishing mortality and guarantee the sustainability of the resource. Nevertheless, the short term and long-term forecast demonstrates us a steady situation of the stock, being possible to reverse the situation of the resource.

- Simulations using both XSA and deterministic a4a models were generally coherent. All the presented scenarios in deterministic models followed the same stock dynamics trends. Using stochastic a4a stock assessment methods increases the uncertainty in the forecast of management scenarios due the introduction of structural and observation uncertainty.

- Comparison between models show us the capability of a4a to replace XSA methods to assess the stock status of the Mediterranean and Black Sea living resources due the similarity between both results. It is necessary to include the uncertainty in the stock assessment parameters to do a development of the statistical stock assessment able to predict the future behaviour of the stock. Uncertainty in stock assessment is key to improve the assessment and management of Mediterranean marine resources. It will help to achieve biomass reference points and, at the end, to build harvest control rules in the GFCM area.

6.- Future steps

Technical activities towards the assessment of management measures could be carried out during further investigations:

- A similar experiment could be carried on comparing the similarities and dissimilarities between both technics (XSA and a4a) in different GSA's and between different kind of fisheries, for example, small pelagic fisheries and to species outside the GFCM study area.
- Trawlers are the main fishing gear who targets European hake, nevertheless, other fishing sectors targets also European hake. An interesting experiment could be to introduce new fishing sectors for the stock assessment of this species.
- Different management scenarios have been tested during the current research. However, no spatial aspects have been assessed. A useful activity could be to incorporate spatial aspects, as for example, the closure of spawning areas as management scenarios.
- Introduction of interaction between species and ecosystem may be useful to achieve better assessment and management results for further investigations.
- An important activity for the application of the methods used during the thesis is the assessment of bioeconomic implications of the simulated scenarios results. Could be useful to test the potential effects of alternative management scenarios on the fishery. Some models as MEFISTO or BEMTOOLS are valuable to achieve this objective.
- Elaborate a harvest control rule for the hake in the Strait of Sicily.

Chapter 2

Calculation of Reference Points in Decreasing Trend Populations

1.- Introduction

The Earth's climate has warmed by approximately 0.6ºC over the past 100 years (Walther *et al.,* 2002). Resolve the effects of climate change in fish populations is complicated. It is due climate change affects a multitude of environmental factors that may affect various processes at different levels of biological organization (Harley *et al.*, 2006). It may be argued that it will be impossible to detect generalities in the response of fish populations to climate change, because the number of influential factors is too large and individual species may differ too widely in their response (Lehodey *et al., 2006*). Effects of climate change are expected to differ in magnitude and direction of among geographic areas (IPCC - Intergovernmental Panel on Climate Change, 2007). Impacts in marine areas remain uncertain. Climate change will affect a range of abiotic factors that are tightly linked to the production and distribution of fish populations. These biotic changes will differ between the open ocean, shelf seas and coastal waters (Walther *et al.* 2002).

In fish, one of the potential impacts of temperature increasing is over the eggs. The temperature increasing has a highly significant effect of decreasing egg incubation time, generating a high increasing of the daily mortality rate of pelagic fish eggs and larvae (Pepin 1991). For example, changes in the physical environment already impacted over cod (*Gadus morhua*) recruitment in the North Sea (Beaugrand 2003). The temperature increasing also produces impacts on primary production and unbalances the whole marine food chain (Brunel & Boucher 2007). Changes in catches of North Sea horse mackerel (*Trachurus trachurus*) (Reid 2001) and Atlantic salmon (*Salmo salar*) (Beaugrand & Reid 2003) were related to changes in the physical environment and in the plankton community (Brunel & Boucher 2007).

Global marine fisheries are underperforming because of overfishing, pollution and other anthropogenic causes. These changes are expected to affect the productivity of marine fisheries leading to losses in revenues, earnings to companies and household incomes (Da Rocha *et al.,* 2014). Recent commitments to adopting an ecosystem approach to fisheries may influence the fact of the reassessment of management targets fitness considering the current scenario with the conservation targets (Worm 2009)

From the management point of view, using a static reference point in a dynamic situation could generate an overestimation of the current stock status. This fact produces also differences in the reference points and causes negative effects in the fisheries management decreasing fishermen's and stockholder's profits.

Summarizing, the growth rate of a fishery resource is subject to changing conditions under global warming. Thus, the population can never be in equilibrium until the ocean temperature stabilises. Technically, global warming alters the steady-state situation. The process is called transitional dynamics (Da Rocha *et al.*, 2014).

This study develops population dynamics of sardine (*Sardina pilchardus*, Walbaum, 1792) in regions VIIIc and IXa by evaluating the consequences for stock assessment and management. The research also compares the differences between the management measures and reference points considering stochastic or deterministic recruitment of the target population. Finally, the study checks the robustness changes of both methods to reduce the uncertainty during the process.

The contribution of this work is to show the benefits of include the population trends into harvest control rules even when it is not possible to estimate the recruitment with perfect accuracy due the existing uncertainty in the stock-recruitment relationship (Ludwig & Walters 1981). The gains from adding the recruitment trend into the management process depends on the accuracy of the estimates. Also, the benefit depends of stock biology.

These results have direct implications for policy making. First, we show that using a HCRs that ignore population trends increases the difficulties to achieve the target point, the stock volatility and underestimates the risk status of the stocks. Second, the necessity of apply a most precautionary approach to avoid the negative implications to the fishery and achieve the highest economic benefit.

2.- Methods

2.1.- Data Acquisition and Study area

The model is applied to (*Sardina pilchardus*, Walbaum, 1792) in ICES VIIIc and IXa sardine (ICES WGHANSA report 2014). The stocks were chosen due to its economic and cultural importance throughout the Portuguese, west coast of French and north Spanish fisheries. The high exploitation and past overfishing (ICES WGHANSA report 2014) of mid-east Atlantic and Cantabrian sea fisheries make them ideal stocks for the assessment and management approach.

The fishery biological parameters information comes from the 2015 ICES Working Group on Southern Horse Mackerel, Anchovy and Sardine (ICES WGHANSA 2015). Most of the parameters had been obtained from Iberian DEPM for estimation of sardine spawning biomass in the IXa-VIIIc and VIIIb up to 45ºN took place in the S and W areas survey done from 15th March to 26th April and from Iberian acoustic survey (PELACUS+PELAGO) to estimate small pelagic fish abundance in IXa and VIIIc.

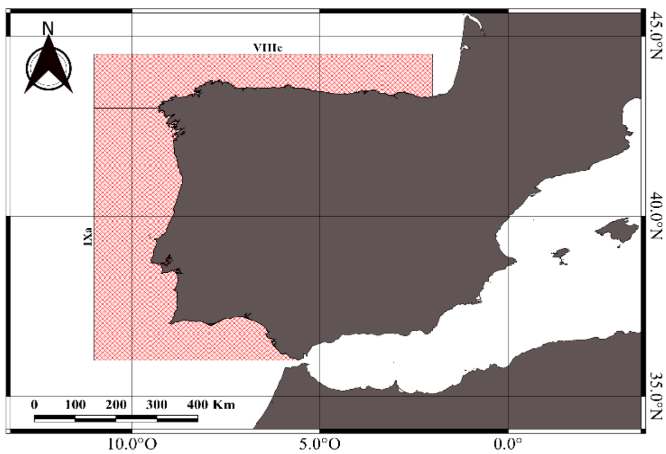


Figure 35 - Study area ICES VIIIc and IXa areas.

Every analysis had been done using "R: A language and environment for statistical computing" software (R Core Team, 2016) and MATLAB.

Table 13 - Age structured model (ICES WGHANSA report 2015. Pag. 222)

2015

Age	N	m_a	Maturity	Weight (Kg)	p_a
0	3623	0.8	0	0	0.039
1	1739	0.5	1	0.028	0.113
2	1082	0.4	1	0.049	0.21
3	398	0.3	1	0.057	0.292
4	150	0.3	1	0.066	0.292
5	65	0.3	1	0.07	0.292
6+	192	0.3	1	0.073	0.087

2.2.- Stock Dynamics

A useful simplification of the biological structure of a fishery is to consider a model with only two ages: Juveniles and adults (Da-Rocha & Mato-Amboage 2016). This simplified system allows to obtain analytical conclusions to be drawn about the relationship between the risk of the stock dropping below the limit reference point and the target reference point.

For the simplification, a stochastic version of Hannesson (Hannesson 1975) fishery based on Beverton and Holt model with two age classes: Juveniles and adults. $N_{t,1}$ and $N_{t,2}$ are the population of juveniles and adults (respectively) in period t. Each year, t, a stochastic exogenous number of juvenile fish are born.

$$N_{t,1} = \exp(Z_t)$$

Where Z_t follows an autoregressive (AR) process:

$$Z_{t+1} = \rho Z_t + \varepsilon_{t+1}$$

With zero mean, $E\varepsilon_{t+1}$ and variance σ_z. The relationship between the number of recruits today and tomorrow is determined by the parameter ρ. Due the unknown relationship stock-recruitment we assume that the number of juveniles is independent of the system spawning stock biomass. In that way, the uncertainty in the process is added simulating a stochastic recruitment.

Additionally, it is assumed that only some of the juveniles survive to become adults in the next period. The dynamics of the second age group are:

$$N_{t+1,2} = N_{t,1} e^{-pF_t - m}$$

Where m is the natural mortality rate and p is the selectivity parameter. The selectivity parameter indicates how the fishing effort affects the fishing mortality of the juveniles.

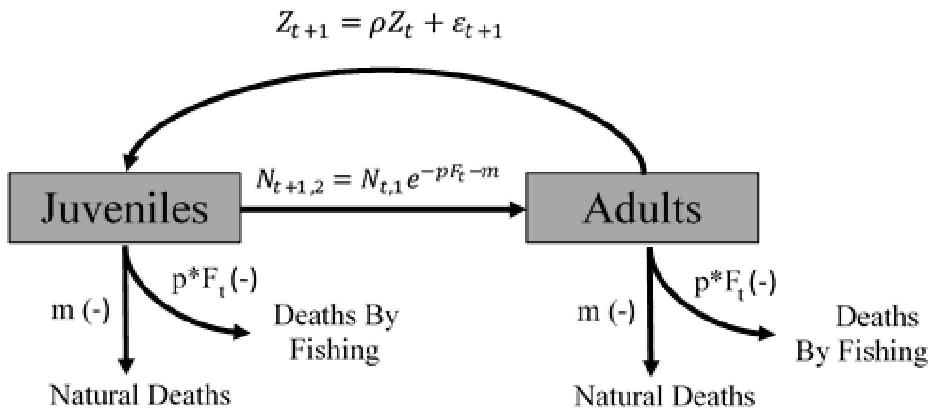


Figure 36 - System dynamics

During the 2-age model example p is unnecessary, without loss of generality we normalize $p = 1$.

To simplify the example, the variables can be changed to define the dynamics in logarithm terms. The stock dynamics become:

$$\log N_1 = z$$

And

$$\log N_2 = x$$

The population could be represented as:

	Time (t)				
Age classes		t	$t+1$	$t+2$	$t+3$
Log juveniles	z	z_t			
Log adults	x		$z_t - F_t - m$		

Finally, the total biomass of the fishery can be defined as:

$$B_t = log\ N_{t,2}$$

The expression implies that a non-constant fraction of adults are spawners and that spawning stock biomass (SSB) is an increasing function of the number of adults in the population.

2.3.- Recruitment Analysis

The trend in the population was analysed using a simple linear regression (PennState 1.1, 2017). The analysis allowed us to summarize the relationship between the number of recruits and the sampled years (Chatterje & Hadi, 2006). Dickey – Fuller test (Dickey & Fuller 1979) was used to test if the unit root is present in an autoregressive model.

$$\begin{cases} \boldsymbol{H_0 = Unit\ Root\ is\ present.\ The\ model\ is\ autoregressive} \\ \boldsymbol{H_1 = Unit\ Root\ is\ not\ present. The\ model\ is\ stationary} \end{cases}$$

To calculate the trend along the time series a Hodrick and Prescott filter (Hodrick & Prescott *et al.*, 1980) was used. This filter allows us to delete the seasonal, irregular and trend components to analyse only the cyclical component. Normal distribution of recruitment timeseries was tested. Logarithm transformation was done in the recruitment series data to fit the data to the normal distribution and apply the filter. Hodrick and Prescott filter allowed us to convert the time series from autoregressive to stationary.

Main problem of decreasing recruitment trend series is related with the manager target to minimize the distance between current reference points value and target reference points value.

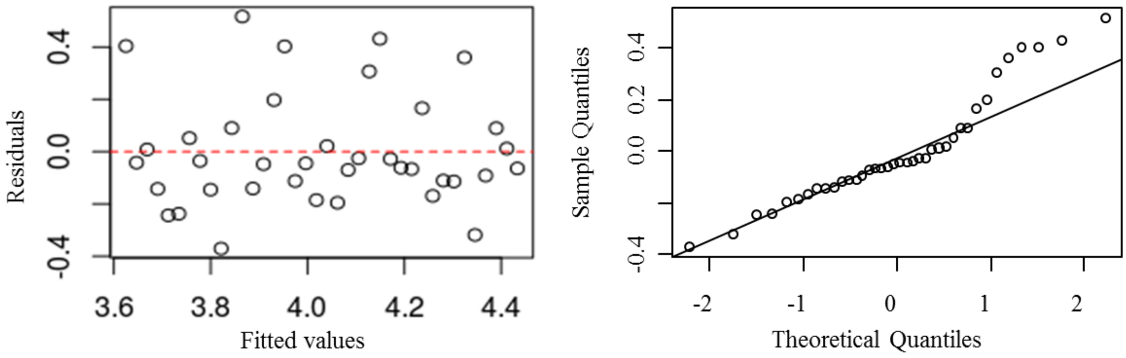


Figure 37 - Hodrick and Prescott filter residuals.

2.4.- Fishery management: The role of λ parameter and effects of different β over the regulator

The current fishery is managed to achieve an exogenous target reference point (for example B_{msy} and the corresponding F_{msy}, $B_{0.1}$ and $F_{0.1}$ or any other exogenous target that represents the manager objectives).

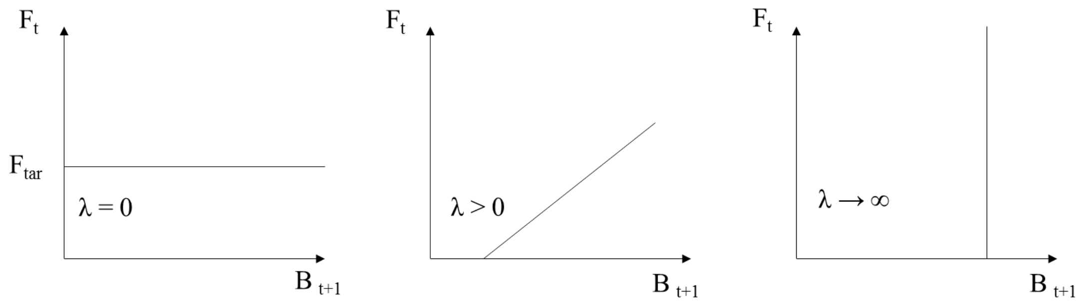


Figure 38 - Different kinds of decision rules as a function of the weight parameter λ in the managers objective function.

The manager's objective is to reduce the distance between the current fishing mortality (F_{curr}) and the current system biomass (B_{curr}) to the target reference point (B_{tar} and F_{tar}), subject to the stock dynamics. In the system, the expectation term is associated to with the stochastic recruitment process. λ parameter weights the importance of reaching the objective and determines the strategy (importance of biomass vs effort oriented objectives). λ value determines the slope of the harvest control rule.

$$\frac{\Delta F_t}{\Delta B_t} = \beta * \lambda$$

$\lambda = 0$	→	Constant Effort: The HCR reproduces a constant fishing mortality rule.
$\lambda > 0$	→	Biological based catch: The HCR reproduces a biomass-based rule.
$\lambda < 0$	→	Constant catch: The HCR generates a negative relationship between fishing and biomass, like a constant catch rule.
$\lambda = \infty$	→	Constant escapement: The HCR reproduces a constant or fixed escapement rule

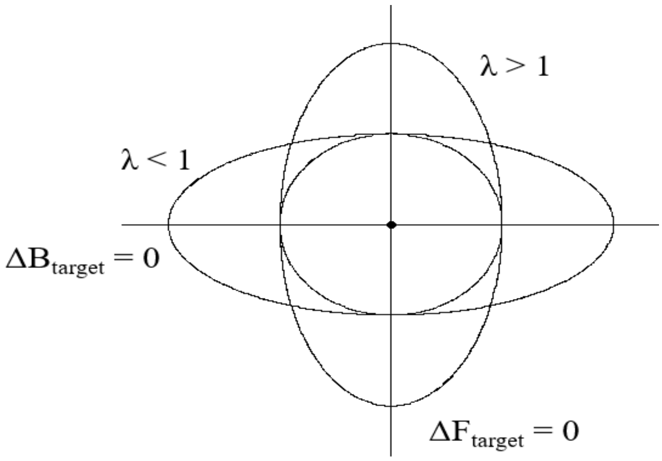


Figure 39 - Different strategies to achieve the target comparison.

The target can be plotted on a 2D graph (Figure 39). It allows to choose the desired gap between the stock status and the target. This gap is given by the weight that the manager has on reaching the effort reference point relative to the biomass target, thus determining whether the fishery is to be managed by effort-focused control rules or biomass control rules.

The profits of the fishery for any period t are given by the difference between revenues and fishing costs. For the shake of simplicity, prices are assumed to be constant over time and total cost to be a convex function (Da Rocha. & Gutierrez 2011).

Note that π_t can be interpreted in several ways from the economic point of view (Da Rocha & Gutierrez 2011). For instance, cost zero (π_t) represents the discounted revenues of the fishery. Alternatively, if the price is one and the cost is zero, represents π_t the discounted yield of the fishery (Da Rocha & Gutierrez 2011).

The objective of the fishery manager is to find the fishing mortality that maximises the present value of the future profits of the fishery. Formally, the present of future profits is given by:

$$J = \sum_{t=0}^{\infty} \beta^t \, \pi_t$$

The parameter $\beta \in [0,1]$ is the discount factor which represents how much the manager is willing to pay to trade-off the value of fishing today against the benefits of increased profits in the future, measured by higher biomass and recruitment (Da Rocha, et al., 2013). Considering $\beta = 1$ implies that managers care about future changes as much as if they occurred during the current year. By contrast, $\beta = 0$ implies not caring about the future at all (Da Rocha *et al.*, 2014).

Therefore, the objective of the fishery managers should be to find the fishing rate trajectory that maximises the present value of the fishery, J, considering that the spawning stock biomass is always greater than the precautionary level, SSB_{pa}. Formally this is a maximization problem.

Summarizing, the HCR for stochastic age-structured models can be defined as the optimal feedback policy that minimizes the weighted sum of squares between the stock assessment outputs and a given "biological reference point".

$$\max_{F_t.B_{t+1}} E_0 \sum_{t=0}^{\infty} -\beta^t \{(F_t - F_{tar})^2 + \lambda(B_t - B_{tar})^2\}$$

$$s.t. \begin{cases} B_{t+1} = z_t - F_t - m \\ z_{t+1} = \rho z_t + \varepsilon_{t+1} \end{cases}$$

The state variables in this problem are $z_t = \log(N_{1,t})$ and $B_t = \log(N_{2,t})$, and F_t is the control variable.

The objective of the approach is to stabilize the resource around a desired point. The HCR is given in terms of the value of a single parameter, λ.

The problem can be simplified with the following change of variables: $\Delta F = F_t - F_{tar}$, $\Delta z_t = z_t - z_{tar}$ and $\Delta B_t = B_t - B_{tar}$. Now the problem can be rewritten as:

$$\max_{\Delta F_t.\Delta B_{t+1}} E_0 \sum_{t=0}^{\infty} -\beta^t \{(\Delta F_t)^2 + \lambda(\Delta B_t)^2\}$$

$$s.t. \begin{cases} \Delta B_{t+1} = \Delta z_t - \Delta F_t \\ \Delta z_{t+1} = \rho \Delta z_t + \varepsilon_{t+1} \end{cases}$$

The dynamics of the stock are independent of the natural mortality parameter m.[2] In that way it is possible to avoid the natural mortality, it is one of the largest sources of uncertainty in the biological dynamics of the stock. Is one of the main advantages of this distance minimization approach. The HCR is robust with respect to that uncertainty. The effect of each HCR is simulated 1000 times.

The problem can easily be converted into an unconstrained deterministic optimization problem. The solution of the unconstrained problem must verify:

$$\max_{\Delta F_t} -\{\Delta F_t^2 + \lambda \Delta B_t^2\} - \beta\{\Delta F_{t+1}^2 + \lambda(\Delta z_t - \Delta F_t)^2$$

The first order condition is

$$\Delta F_t - \beta\lambda(\Delta z_t - \Delta F_t) = 0$$

Solving for the HCR, ΔF_t, we have:

[2] This occurs when, $B_{t+1} - B_{tar} = (z_t - F_t - m) - (z_{tar} - F_{tar} - m)$

$$\Delta F_t = \frac{\beta\lambda}{1+\beta\lambda}\Delta z_t$$

Which is linear in the state variable Δz_t. Combining the HCR with the dynamics of the stock, $\Delta B_{t+1} = \Delta z_t - \Delta F_t$, we have:

$$\Delta B_{t+1} = \frac{\beta\lambda}{1+\beta\lambda}\Delta z_t$$

From this model, it is possible to start drawing conclusions on the impact of recruitments and possible implications of the model parameters for the design of the HCR. Firstly, good recruitments imply higher fishing mortality. Secondly, whatever the spawner biomass level is, good recruitment in the last year implies higher fishing mortality, even if the biomass level is lower than B_{tar} (Tahvonen 2009 and Tahvonen 2009).

2.5.- Yield

It was characterized a dynamic optimal harvesting that maximizes discounted utility assuming a stochastic age-structured framework based on Baranov's catch equation. The purpose of it is calculate the yield for the 2 age-class model. The yield in value of age $a = 1,2$, for year t is:

$$Y_t^a = y_t^a(F_t)N_t^a$$

Were,

$$y_t^a(F_t) = pr^a\omega^a \frac{p^aF_t}{m+p^aF_t}[1- e^{-(p^aF_t+m)}]$$

Determining the net present value of the fishery yield by

$$\sum_{t=0}^{\infty}\beta^t[y_t^1(F_t) + y_t^2(F_t)N_t^2(F_{t-1})]$$

Where $0 < \beta^t < 1$ is the discount factor.

This allows us to compare optimal harvesting in a discounted economic context with standard reference points used by fisheries agencies for long term management plans like, for example, F_{msy} or F_{pa}. The ICES advice is based on a stationary sustainable yield where F_{msy} is considered the main target reference point to be reached by the fishery in the long term if the SSB is above the limit reference point B_{pa}.

2.6.- Harvest control rules and risk

An important question by fisheries managers is: What is the probability of population dropping below the reference points boundaries? Is important avoid the situation of stock dropping below precautionary boundaries. All combinations of reference points and harvest control rules are not linked with an acceptable risk level. For example, in the desired case of decrease the fishery risk level keeping constant maximum sustainable yield levels, the harvest control rule should be changed to heavier older individuals. At the same time, if the target is B_{msy}, managers should not swap to a constant effort harvest control rule to avoid the overfishing risk.

During the current research, recruitment decreasing trend is due an obvious overfishing problem along the years or due a F_{max} based exploitation instead of a more precautionary approach. This experiment wants to compare 2 management scenarios under a non-precautionary target point.

The fact of not considering a decreasing recruitment trend mainly will generate: i) An increase in the model error, ii) increased uncertainty and iii) increased gaps between target and current fishery situation.

2.7.- Trend effects over reference points

To follow the explained approach, it is necessary that the recruit number today should be the same that the number of recruits tomorrow plus a random error. Mathematically expressed is:

$$Recruits_{(t+1)} = Recruits_t + \varepsilon$$

If this condition does not comply, it affects to our management strategy i) increasing the HCR error (Figure 40), ii) increasing the model uncertainty and iii) modifying distance of current situation to the management target.

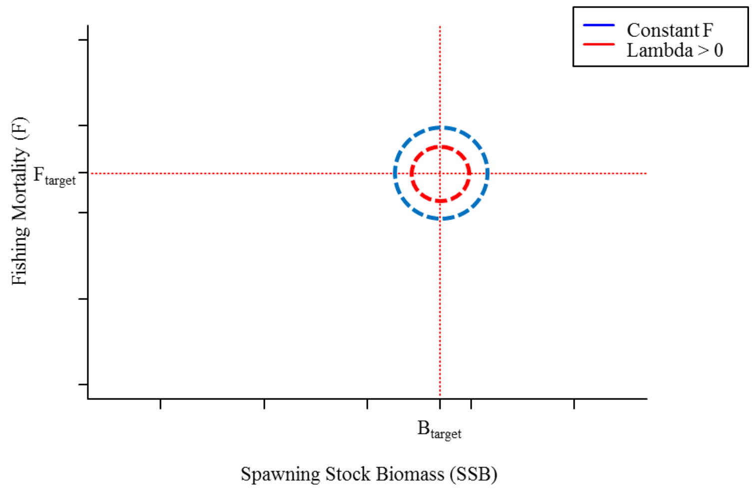


Figure 40 - Standard error comparison. Constant F Vs Lambda > 0

Also, the fact of not considering recruitment trend during management process will generate differences in the "safe fishing area" representation. Our main intuition during the development of the thesis is that constant F harvest control rule will produce differences in the perception of safe fishing area, generating unexpected results in the target fishery (Figure 41).

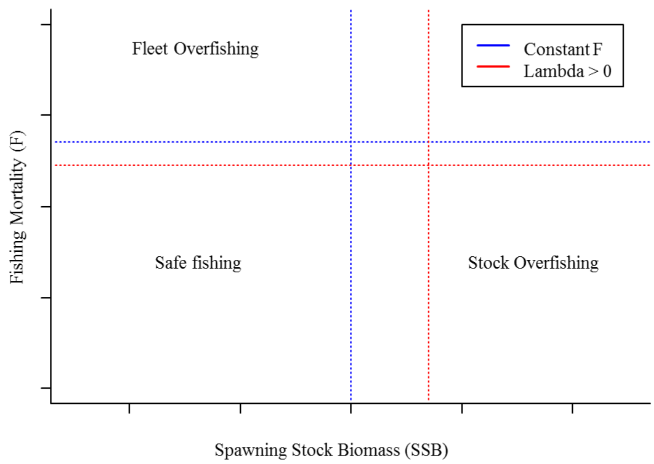


Figure 41 - Different sustainable management areas between both strategies.

3.- Results

3.1.- Recruitment analysis

Logarithm of recruit number and (1+SSB) showed a decreasing trend of 2.18% and 9.48% respectively. It means that the recruitment trend it is due a drop of the spawning stock biomass (SSB).

Dickey Fuller test showed us the recruitment data series autoregressive component. For the Dickey – Fuller test, $p.value = 0.528 > \alpha = 0.05$. Null hypothesis is accepted. Thus, the logarithm of recruitment data series is autoregressive.

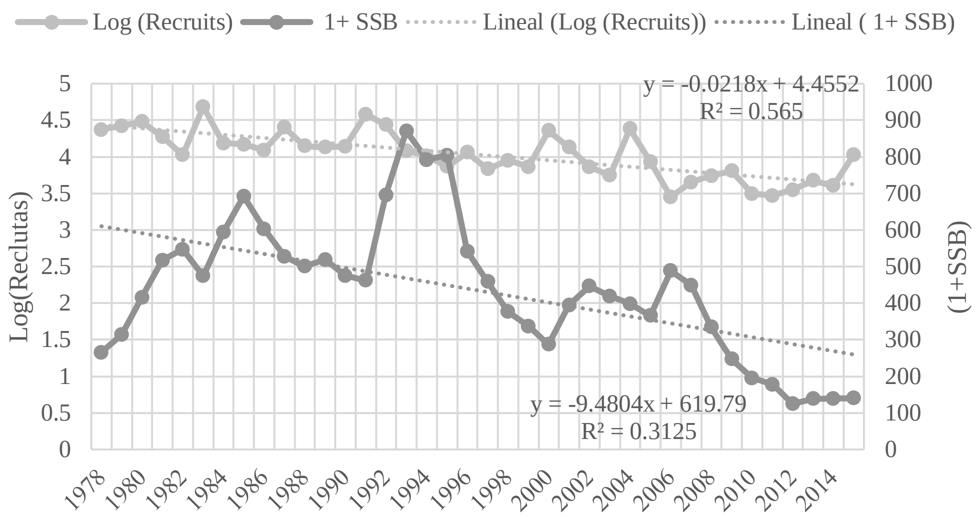


Figure 42 - Recruitment trend

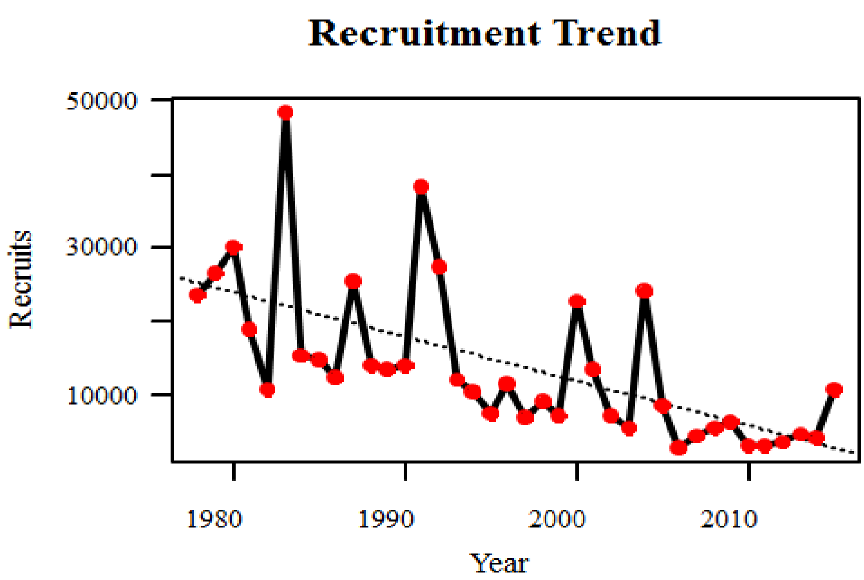


Figure 43 - Isolated recuitment trend

Seasonal, irregular and trend components removal Hodrick and Prescott filter was applied (Figure 44) to rebuild the problem in a stationary problem.

Trend in recruitment series was successfully removed (Figure 44 – right-handed figure) and the shocks or extra economic and casual components were deleted of the timeseries. This analysis allowed us to achieve more consistent results with the observed data.

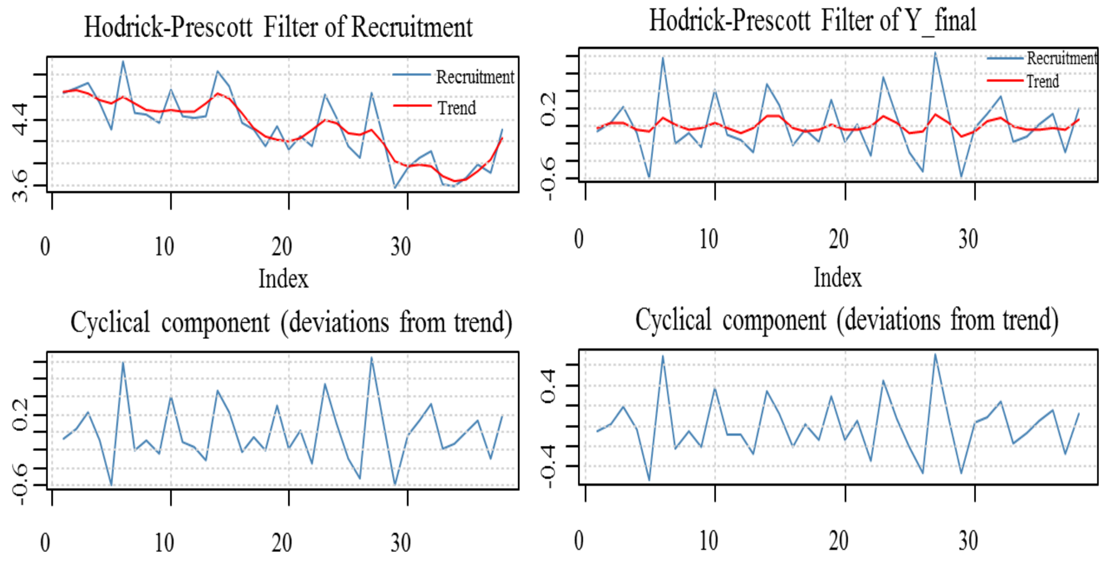


Figure 44 - Top left panel shows differences between recruitment and trend. Bottom left shows cyclical component of the recruitment series. Top right shows the soft recruitment series removing the trend from the series.

3.2.- F_{max} and yield

F_{max} (2.480) was obtained as a target reference point.

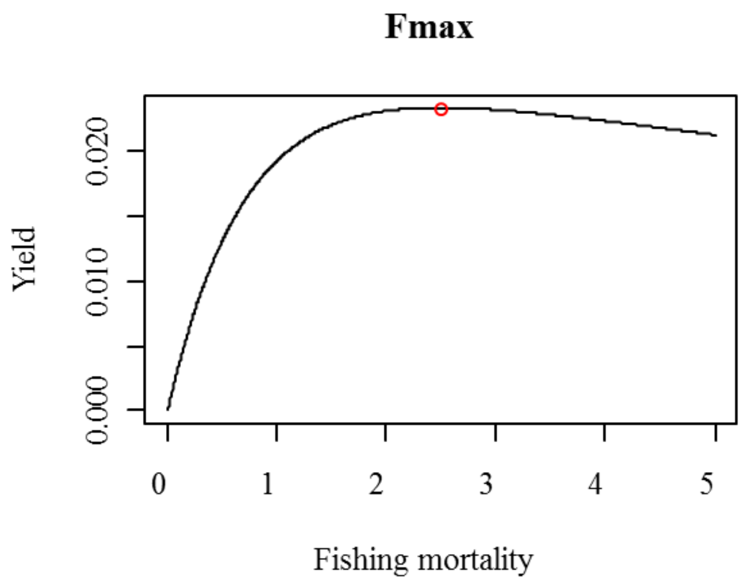


Figure 45 - Fmax reference point

In the concrete case of setting F_{max} as a target of fishing mortality it may occur that the yield is not maximized. (Da Rocha *et al.*, 2013) show that F_{max} is not the optimal solution to the maximization problem.

3.3.- Comparison of Harvest Control Rules: Constant effort versus Biological based catch.

- **Stock volatility and target points:** Comparing the results obtained for the SSB volatility for both management strategies, for "Constant F" (Not trend consideration) there are not volatility changes (standard deviation = 0) while, taking care about recruitment trend (Lambda > 0), volatility increases to 0.0548. Thus, not include the recruitment trend in the management process ignores part of the risk of your management strategy.
- **Stock volatility and HCR:** Higher biomass weight decreases the volatility. That is, the higher λ, the lower volatility. The values of the standard deviation in SSB go from 0.0185 to 0.0170 for constant F scenario and for biomass based harvest control rule respectively. In terms of volatility, a constant effort harvest control rule is the worst strategy.
- **Target points and yield:** As we can see in table 14, yield is higher in constant F harvest control rule than in biomass based harvest control rule (0.0309 and 0.0307 respectively)
- **Harvest control rule and risk:** Taking care about the trend in the fishery management process reduces the probability of exceed the precautionary boundary $B < 0.5\ B_{max}$.

Table 14 - Numerical experiment to evaluate the implications between HCR, reference points and risk.

	Constant F (λ = 0)	**λ > 0**
Fishing mortality	2.4800	2.4814
Standard deviation	0.0000	0.0548
SSB	0.0454	0.0449
Standard deviation	0.0185	0.0170
Yield per recruit	0.0309	0.0307
Standard deviation	0.0121	0.0117
Risk (Probability of $B < 0.5\ B_{max}$)	0.0100	0.0036

Figure 46 shows the effective fisheries management for sardine. Biological based HCR increases the safe management area of the fishery. Constant fishing mortality HCR decreases the risk of get into a fleet overfishing situation. Nevertheless, constant fishing mortality HCR increases the risk on falling into a stock overfishing. It is logical due the fact that during next year you will have less sardine than the past caused by the negative recruitment trend.

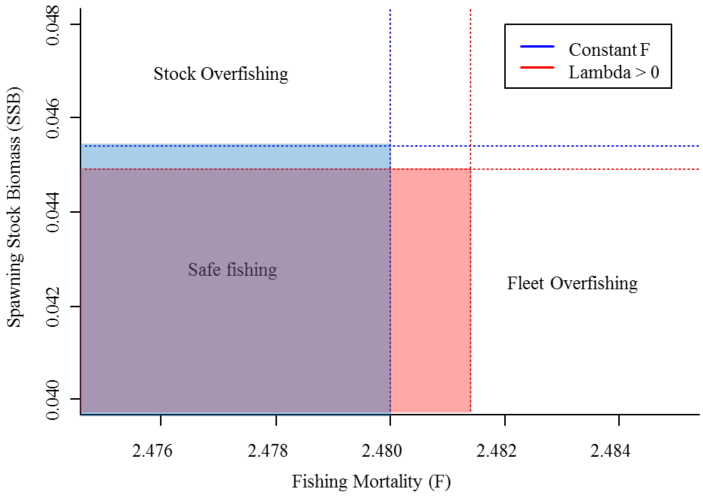


Figure 46 - Different Safe fishing areas for both HCR strategies. In lambda > 0 we could see that the safe fishing area is bigger than in Constant F strategy.

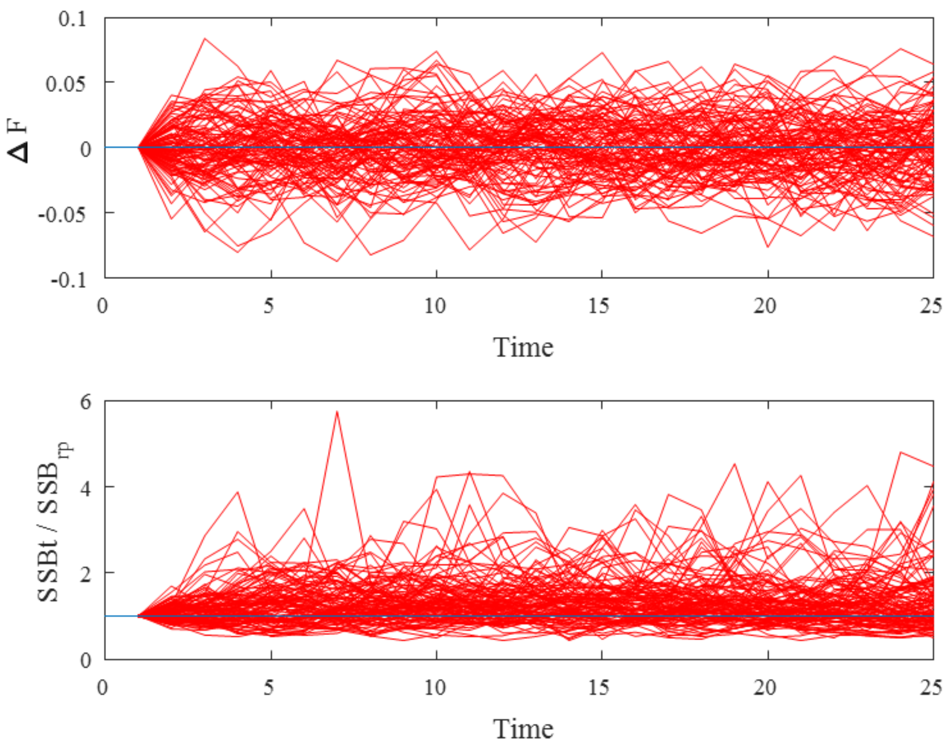


Figure 47 - Results of the 1000 HCR simulations. Top graph represents the possible fishing mortality fluctuations under a biomass based harvest control rule during 25 simulated years. Bottom graph represents the fluctuations in target spawning stock biomass / cur

4.- Discussion

Responses by individual species to climate change may disrupt their interactions with others at the same or adjacent trophic levels (Walther *et al.,* 2002). Recruitment in fish populations has long been known to be a key process that is strongly influenced by climate variability (Walther *et al.,* 2002). Global warming is the main effect of climate change. Although climate change generates widespread effects on marine and stock dynamics, global warming does not necessarily lead to a monotonic decrease in the expected biomass levels.

Increases in the surface temperature of the Iberian Atlantic fishery ground are compatible with higher expected biomass and economic profit levels when the resource is optimally exploited (Da Rocha & Gutierrez 2011). Also, small pelagic species are subject to other environmental factors apart from temperature changes that affect natural productivity. Summarizing, sardine biomass is affected by other environmental variables that can mitigate the reduction in natural growth caused by climate change (Da Rocha & Gutierrez 2011) being possible to manage in a sustainable and high profitable way.

Climate change may have a large impact on the distribution of maximum catch potential (as a proxy of potential fisheries productivity) (Cheung *et al.* 2010) and has direct implications in the calculus of management reference points. During the investigation was demonstrated that a strong fishery stock dynamics knowledge could be translated in better management measures and increase of economical profit for the fisherman's, avoiding the risk of collapse.

Stock dynamics are key to achieve a better management of the fishery. As we demonstrated during the research, ignore the recruitment trend during the stock assessment and management process generates an overestimation of the reference point and ignores part of the risk of the harvest strategy. Therefore, summarizing, neglecting the biological structure of the resource results in an underestimation of the optimal fishing mortality (Tahvonen 2009).

Reference points are one of the main tools used by fishery managers to make decision about the future catch options (Da Rocha 2012). For example, the European Union, through the Common Fisheries Policy (CFP), wanted all the stock to be fished at F_{MSY} by 2015.

During the investigation, we demonstrated that F_{max} is not an adequate management reference point for fisheries. F_{max} reference point could lead to overexploitation of the stock and subsequently to an underperforming of the target fishery. As basic information, we recommend a more precautionary reference point to avoid an overexploitation situation of the resource and ensure the sustainability of the fishery.

The proposition of elaborate a biomass based harvest control rule has direct implications in policy design. All fisheries are managed to avoid the risk of the stock collapsing, the aim should be to design policies that assign more weight to biomass goals (like a biomass based HCR or constant escapement rules) (Da-Rocha & Mato-Amboage 2016). At the same time, constant fishing harvest control rule implementation amplifies future risk by increasing the biomass volatility of the stock (Da-Rocha & Mato-Amboage 2016). Being the risk higher in constant F control policies, management politics as total allowable catches and fixed quotas are not optimal (Da-Rocha & Mato-Amboage 2016).

In practical terms, it is hard to create a management strategy under the umbrella of a biomass based harvest control rule. An easier way to implement these kinds of measures in our fishery is a more precautionary harvest strategy taking as a reference a more precautionary reference point. Other alternatives as reference point as $2/3F_{msy}$, $3/F_{msy}$ or $90\%F_{msy}$ could be optimal for the future of the fishery.

5.- Conclusions

Modern fisheries management is moving towards a precautionary approach to ensure the sustainability of the marine resurces (ICES, 1997). During this work, for *Sardina pilchardus* in ICES VIIIc and IXa was demonstrated the risk of using F_{max} as a target reference point in the stock management and the necessity of being more precautionary during the fishery management process.

Main outputs of the investigation were:

- Not include recruitment trend during the management of the fishery ignores part of the risk of manage your fishery taking as a reference point a constant F value.
- Biomass based harvest control rule decreases the probability of biommass dropping under your $B_{trigger}$ reference point. Constant fishing mortality harvest control rule increases the risk of collapse of the fishery.
- Ignore the recruitment trend overestimates the yield per recruit value of the fishery. Biomass based harvest control rule is more accurate to estimate the future yield of the fishery.

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Annex – Codes Chapter 1

1.- Extended Survivor Analysis

```
library(FLCore)
library(FLEDA)
library(FLXSA)
library(FLAssess)
library(FLash)
require(ggplotFL)
require(plyr)
require(FLBRP)

#read stock file
aa.stk <- readFLStock("HKE1216.IND", no.discards=TRUE)
catch(aa.stk)
landings(aa.stk)

catch(aa.stk)/landings(aa.stk)

# catch.n(aa.stk)
# landings.n(aa.stk)
# catch.wt(aa.stk)
# landings.wt(aa.stk)
# quantSums(catch.n(aa.stk)*catch.wt(aa.stk))

bubbles(age~year, data=(catch.n(aa.stk)), bub.scale=5)
bubbles(age~year, data=(catch.wt(aa.stk)), bub.scale=5)
mat(aa.stk)
m(aa.stk)

##### SOP correction
sop(aa.stk,"landings")
```

```
landings(aa.stk)*sop(aa.stk,"landings")

landings(aa.stk)<-catch(aa.stk)
landings(aa.stk)/catch(aa.stk)
#set up the stock
units(harvest(aa.stk))<-"f"
range(aa.stk)["minfbar"] <- 1
range(aa.stk)["maxfbar"] <- 5

#Set the plus group
aa.stk <- setPlusGroup(aa.stk, 6)

# #Remove 2003
# aa.stk<-window(aa.stk, start=2004, end=2013)

#read index (tuning file)
aa.idx <- readFLIndices("TUNEFF.dat")

#Remove age until 4
# aa.idx<-window(aa.idx, start=2005, end=2013)
aa.idx[[1]]<- trim(aa.idx[[1]], age=0:2)

bubbles(age~year, data=(index(aa.idx[[1]])), bub.scale=6)

#plot the stock
plot(aa.stk)

######################################
#######################################
#### sensitivity analisys changing rage different setting changing  rage
########################################
```

```
#FSE 0.5
FLXSA.control.aa <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=0.5,
                    rage=0, qage=1, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
                    window=100, tsrange=20, tspower=3, vpa=FALSE)

FLXSA.control.aa1 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=0.5,
                    rage=0, qage=2, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
                    window=100, tsrange=20, tspower=3, vpa=FALSE)

FLXSA.control.aa2 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=0.5,
                    rage=0, qage=3, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
                    window=100, tsrange=20, tspower=3, vpa=FALSE)

FLXSA.control.aa3 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=0.5,
                    rage=0, qage=4, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
                    window=100, tsrange=20, tspower=3, vpa=FALSE)
#FSE 1
FLXSA.control.aa4 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=1,
                    rage=0, qage=1, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
                    window=100, tsrange=20, tspower=3, vpa=FALSE)

FLXSA.control.aa5 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=1.0,
                    rage=0, qage=2, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
                    window=100, tsrange=20, tspower=3, vpa=FALSE)
```

```
FLXSA.control.aa6 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=1,
    rage=0, qage=3, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
    window=100, tsrange=20, tspower=3, vpa=FALSE)

FLXSA.control.aa7 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=1,
    rage=0, qage=4, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
    window=100, tsrange=20, tspower=3, vpa=FALSE)

#FSE 2
FLXSA.control.aa8 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=2,
    rage=0, qage=1, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
    window=100, tsrange=20, tspower=3, vpa=FALSE)

FLXSA.control.aa9 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=2.0,
    rage=0, qage=2, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
    window=100, tsrange=20, tspower=3, vpa=FALSE)

FLXSA.control.aa10 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=2,
    rage=0, qage=3, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
    window=100, tsrange=20, tspower=3, vpa=FALSE)

FLXSA.control.aa11 <- FLXSA.control(x=NULL, tol=1e-09, maxit=30, min.nse=0.3, fse=2,
    rage=0, qage=4, shk.n=TRUE, shk.f=TRUE, shk.yrs=3, shk.ages=3,
```

```
                          window=100, tsrange=20, tspower=3, vpa=FALSE)


#Running the assessments with different settings changing q at age
aa.xsa <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa)
aa.xsa1 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa1)
aa.xsa2 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa2)
aa.xsa3 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa3)
aa.xsa4 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa4)
aa.xsa5 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa5)
aa.xsa6 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa6)
aa.xsa7 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa7)
aa.xsa8 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa8)
aa.xsa9 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa9)
aa.xsa10 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa10)
aa.xsa11 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa11)

#Add the results to the stock files
aa.stk <- aa.stk+aa.xsa
aa.stk1 <- aa.stk+aa.xsa1
aa.stk2 <- aa.stk+aa.xsa2
aa.stk3 <- aa.stk+aa.xsa3
aa.stk4 <- aa.stk+aa.xsa4
aa.stk5 <- aa.stk+aa.xsa5
aa.stk6 <- aa.stk+aa.xsa6
aa.stk7 <- aa.stk+aa.xsa7
aa.stk8 <- aa.stk+aa.xsa8
aa.stk9 <- aa.stk+aa.xsa9
aa.stk10 <- aa.stk+aa.xsa10
aa.stk11<- aa.stk+aa.xsa11
```

```
stocks <- FLStocks(aa.stk,aa.stk1,aa.stk2,aa.stk3,aa.stk4,aa.stk5,aa.stk6,aa.stk7,aa.stk8,aa.stk9,aa.stk10,aa.stk11)

names(stocks)<- c("0.5r0q1","0.5r0q2","0.5r0q3","0.5r0q4","1r0q1","1r0q2","1r0q3","1r0q4",
              "2r0q1","2r0q2","2r0q3","2r0q4")

plot(stocks)

plot(aa.stk+aa.xsa4)
```

2.- Deterministic a4a

```
# MI PROYECTO:

#1.- Paquetes:

library(FLa4a)
library(XML)
library(reshape2)
library(diagram)
library(plot3D)
library(FLCore)
library(FLXSA)
library(ggplotFL)
library(ggplot2)

#
rm(list=ls())
cat("\014")
#

# Working Directory

setwd("~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Length structured/Deterministic a4a")
getwd()

# Leemos todos los archivos:

# read stock file
HKE.stk <- readFLStock("HKE1216.IND", no.discards=T)

# Set up the stock (create the empty matrix)
```

```
units(harvest(HKE.stk))<-"f"
range(HKE.stk)["minfbar"] <- 2
range(HKE.stk)["maxfbar"] <- 4

# Set the plus group
HKE.stk <- setPlusGroup(HKE.stk, 7)

# read index (tuning file)
HKE.idx <- readFLIndices("TUNEFF.DAT")
HKE.idx <- FLIndices(trim(HKE.idx[[1]],age=1:7))
bubbles(age~year, data=(index(HKE.idx[[1]])), bub.scale=10)

plot(HKE.stk)

catch.n(HKE.stk)[catch.n(HKE.stk)==0] <- 0.01
for (i in 1:length(HKE.idx)){
  index(HKE.idx[[i]])[index(HKE.idx[[i]])==0] <- 0.01
}
# 5.- CORRIENDO EVALUACIONES
```

En el modelo de evaluacion a4a, la estructura del modelo esta definida por submodelos,

los cuales son varias artes de un modelo de captura por edad que requiere varias asumpciones.

Estos son los 5 submodelos:

Modelo para F-at-age

Modelo para la estructura de edad inicial

Modelo para el reclutamiento

Una lista de modelos para la observacion de la varianza de la captura por edad e indices de abundancia

Llevado a la practica: Fijamos los modelos de varianza y los modelos de estructura de edad iniciales,

pero esto en teoria puede cambiar

Los submodelos usan modelos lineales.

Existen 2 tipos de evaluaciones disponibles en a4a:

Ajuste del proceso de gestion: No estima ni computa covarianzas y es mas rapido de ejecutar

Ajuste completo de la evaluacion: Nos devuelve parametros y sus covarianzas y tarda mas tiempo en ajustar

5.1.- Stock assessment model details

El modelo estadistico de captura por edad esta basado en la ecuacion de Baranov de captura y en el indice de capturabilidad.

Todos los detalles de las ecuaciones estan en el manual (pag.37)

5.2.- Rapido y sucio

He aqui un ejemplo de uso del modelo de evaluacion. Se ve como los ajustes default del modelo de ev. funcionan bien.

fit <- sca(HKE.stk, HKE.idx)

Para inspeccionar el resumen de la evaluacion del stock, el cual esta construido con tendencias de:

mortalidad pesquera,

desove,

ssb,

captura y

reclutas

El usuario debe anadir el objeto a4afit al archivo original FLStock usando el + method

```
fit <- sca(HKE.stk, FLIndices(HKE.idx))


fmod2 <- ~ s(age, k=3) + s(year, k = 3)
qmodel <- list(~ factor(age))
srmodB <- ~ bevholt(CV=0.1)
fit <- sca(HKE.stk, FLIndices(HKE.idx), fmodel=fmod2,qmodel=qmodel,srmodel=srmodB)
stk <- HKE.stk + fit
plot(stk)


persp3D(z=harvest(fit)[drop=TRUE], x=as.numeric(dimnames(harvest(fit))[[1]]), y=as.numeric(dimnames(harvest(fit))[[2]]), facets = FALSE, curtain = TRUE)

ribbon3D( z = stock.n(fit)[drop=TRUE], x= as.numeric(dimnames(stock.n(fit))[[1]]), y= as.numeric(dimnames(stock.n(fit))[[2]]), facets = FALSE, curtain = TRUE)

# 5.3- Diagnosticos

# Un conjunto de graficos que sriven para comprobar la calidad de las asumpciones se encuentra implementado.
# Lo mas normal es mirar los log-residuales estandarizados para ver los resultados parciales de grandes varianzas.
# Hay que recordad que la estandarizacion tiene que dar residuales con varianza 1.
# Estos resultados permiten al usuario identificar desviaciones de la asumpcion lognormal.

res <- residuals(fit,HKE.stk,HKE.idx)

bubbles(res)
```

```
qqmath(res)

plot(fit,HKE.stk)

plot(fit, HKE.idx)
```

Para obtener la informacion sobre la probabilidad hay que ajustar el metodo fitSumm()

Este metodo nos va a ayudar a extraer la informacion sobre la probabilidad, numero de parametros...

Los metodos AIC() y BIC() nos ayudaran a computar la informacion criterio.

```
fitSumm(fit)

AIC(fit)

BIC(fit)
```

3.- Stochastic a4a Analysis

```
############################################################
###                                   ###
###          "THE SCRIPT" - MAY 2017          ###
###     Eduardo Sánchez Llamas - Master Thesis     ###
###                                   ###
###                a4a                   ###
############################################################

# SCRIPT INDEX (GENERAL)

# install.packages(c("copula","triangle"))
# install.packages(c("FLCore", "FLa4a"), repos="http://flr-project.org/R")

library(FLa4a)
library(XML)
library(reshape2)
library(plot3D)
library(FLCore)
library(FLXSA)
library(ggplotFL)

#
rm(list=ls())
cat("\014")
#

setwd("~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Stochastic a4a/Data")

#setwd("~/HAKE 12-16/MSE-StrategyXSA/Length structured")
```

```
#################################################################
#################
##                                        ##
##                  Functions                   ##
##                                        ##
#################################################################
#################

# recode Gadget's length categories
qt2qt <- function(object, id=5, split="-"){
  qt <- object[,id]
  levels(qt) <- unlist(lapply(strsplit(levels(qt), split=split), "[[", 2))
  as.numeric(as.character(qt))
}
# function to check import and do some massage
cim <- function(object, n, wt, hrv="missing"){
  v <- object[sample(1:nrow(object), 1),]
  c1                                                                    <-
c(n[as.character(v$V5),as.character(v$V1),1,as.character(v$V2)]==v$V6)
  c2                                                                    <-
c(wt[as.character(v$V5),as.character(v$V1),1,as.character(v$V2)]==v$V7)
  if(missing(hrv)){
    c1 + c2 == 2
  } else {
    c3                                                                  <-
c(hrv[as.character(v$V5),as.character(v$V1),1,as.character(v$V2)]==v$V8)
    c1 + c2 + c3 == 3
  }
}
# plot for S4 data structures with diagram
plotS4 <- function(object, linktext="typeof", main="S4 class", ...){
  6
  args <- list(...)
  obj <- getClass(as.character(object))
```

```
  df0 <- data.frame(names(obj@slots), unlist(lapply(obj@slots, "[[", 1)))
  nms <- c(t(df0))
  nslts <- length(nms)/2
  M <- matrix(nrow = length(nms), ncol = length(nms), byrow = TRUE, data = 0)
  for(i in 1:nslts){
    M[i*2,i*2-1] <- linktext
  }
  args$A=M
  args$pos=rep(2, length(nms)/2)
  args$name = nms
  args$main=main
  do.call("plotmat", args)
}

##################################################################################
##                                          ##
##              Introducing Data                  ##
##                                          ##
##################################################################################



# Catch


cth.orig <- read.table("cth_mean_weight_kg_review.txt", header=FALSE,skip=5,fill = TRUE)
head(cth.orig)
cth.orig[,5] <- qt2qt(cth.orig)
cth.n <- acast(V5~V1~1~V2~1~1, value.var="V6", data=cth.orig)
cth.wt <- acast(V5~V1~1~V2~1~1, value.var="V7", data=cth.orig)
dnms <- dimnames(cth.n)
names(dnms) <- names(dimnames(FLQuant()))
```

```
names(dnms)[1] <- "len"
cth.n <- FLQuant(cth.n, dimnames=dnms)
cth.wt <- FLQuant(cth.wt, dimnames=dnms)

HKE.stk <- FLStockLen(catch.n=cth.n,
                      catch.wt=cth.wt)

cim(cth.orig,cth.n,cth.wt)

HKE.stk <- FLStockLen(catch.n=cth.n,catch.wt=cth.wt)

# Survey

idx.orig <- read.table("idx_mean_weight_kg.txt", skip=5, header=FALSE, fill = TRUE)
idx.orig[,5] <- qt2qt(idx.orig)
idx.n <- acast(V5~V1~1~V2~1~1, value.var="V6", data=idx.orig)
idx.wt <- acast(V5~V1~1~V2~1~1, value.var="V7", data=idx.orig)
dnms <- dimnames(idx.n)
names(dnms) <- names(dimnames(FLQuant()))
names(dnms)[1] <- "len"
idx.n <- FLQuant(idx.n, dimnames=dnms)
idx.wt <- FLQuant(idx.wt, dimnames=dnms)
HKE.idx <- FLIndex(index=idx.n, catch.n=idx.n, catch.wt=idx.wt)
effort(HKE.idx)[] <- 100


m(HKE.stk)[]<-0.05
mat(HKE.stk)[]<-m.spwn(HKE.stk)[]<-harvest.spwn(HKE.stk)[]<-0

## careful, landings are not retained in the stock object after length to age conversion
```

```
landings(HKE.stk)[]<-
c(3792.2,3395.5,3284.4,3444.7,2532.8,3306.1,3467.4,4415.0,4081.8)

#################################################################
#################

##                                                          ##

##          Adding uncertainty to growth parameters          ##

##                                                          ##

#################################################################
#################

#Von Bert. Model

vbObj <- a4aGr(
  grMod=~linf*(1-exp(-k*(t-t0))),
  grInvMod=~t0-1/k*log(1-len/linf),
  params=FLPar(linf=100, k=0.116, t0=-0.6, units=c("cm","ano-1","ano"))
)

lc=100
predict(vbObj, len=lc)

predict(vbObj, t=predict(vbObj, len=lc))

predict(vbObj, len=5:20+0.5)
predict(vbObj, t=1:20+0.5)

prediction <- predict(vbObj, len=seq(8, 74, length = 200))

predictiontime <- predict(vbObj, t=seq(0.1,10, length=200))

plot(seq(8, 74, length = 200), prediction, xlab="length (cm)", ylab="Age (years)")
```

```
plot(seq(0.1,10, length=200), predictiontime, ylab="length (cm)", xlab="Age (years)")


################################################
##                              ##
## Ages without uncertainty:                ##
## cth.n <- l2a(catch.n(HKE.stk), vbObj)    ##
##                              ##
################################################


# 3.2.- AÑADIENDO INCERTIDUMBRE CON LA DISTRIBUCIÓN NORMAL MULTIVARIANTE
# Adding uncertainty with a normal multivariate distribution
cm <- diag(c(1,1,1))


cm[1,2] <- cm[2,1] <- -0.5


cv <- 0.2


p <- c(linf=100, k=0.116, t0=-0.6)
vc <- matrix(1, ncol=3, nrow=3)
l <- vc
l[1,] <- l[,1] <- p[1]*cv
k <- vc
k[,2] <- k[2,] <- p[2]*cv
t <- vc
t[3,] <- t[,3] <- p[3]*cv
mm <- t*k*l
diag(mm) <- diag(mm)^2
mm <- mm*cm



all.equal(cm, cov2cor(mm)) # Correlation = "True"
```

```
vbObj <- a4aGr(grMod=~linf*(1-exp(-k*(t-t0))),
        grInvMod=~t0-1/k*log(1-len/linf),
        params=FLPar(linf=p["linf"], k=p["k"], t0=p["t0"], units=c("cm","ano-1","ano")), vcov=mm)

# Data is following a normal multivariate distribution

vbObj@params

dim(vbObj@params)

# Simulating 1000 iterations:

vbNorm <- mvrnorm(10000,vbObj)

vbNorm@params

dim(vbNorm@params)

ages <- predict(vbNorm, len=5:10+0.5)
dim(ages)

ages[,1:10]

par(mfrow=c(1,1))
hist(c(params(vbNorm)["linf",]), main="linf", xlab="")
hist(c(params(vbNorm)["k",]), main="k", prob=TRUE, xlab="")
hist(c(params(vbNorm)["t0",]), main="t0", xlab="")

splom(data.frame(t(params(vbNorm)@.Data)), pch=".",par.settings=list(plot.symbol=list(pch=50, cex=1.5, col=1)))
```

```
boxplot(t(predict(vbNorm, t=0:25+0.5)),xlab="Years",ylab="Length")

#################################################################
#################
##                                                    ##
##              Natural Mortality matrix uncertainty           ##
##                                                    ##
#################################################################
#################

shape4 <- FLModelSim(model=~exp(-age-0.5))
level4 <- FLModelSim(model=~k^0.66*t^0.57,
        params=FLPar(k=0.116, t=10),
        vcov=array(c(0.002, 0.01,0.01, 1), dim=c(2,2)))
trend4 <- FLModelSim(model=~1+b, params=FLPar(b=0.5), vcov=matrix(0.02))

m4 <- a4aM(shape=shape4, level=level4, trend=trend4)
m4 <- mvrnorm(250,m4)
m4
m4@level
params(trend(m4))
m4 <- a4aM(shape=shape4, level=mvrnorm(100,level4),trend=mvrnorm(100,trend4))
params(shape(m4))

#

linf <- 100
k <- 0.116

mm <- matrix(NA, ncol=2, nrow=2)
diag(mm) <- c((linf*0.1)^2,(k*0.1)^2)
mm[upper.tri(mm)] <- mm[lower.tri(mm)] <- c(0.05)
```

```
cov2cor(mm)

mgis2 <-
FLModelSim(model=~k*(linf/len)^1.5,params=FLPar(linf=linf,k=k),vcov=mm)
pars <- list(list(a=90,b=110), list(a=0.05,b=0.15,c=0.110))
mgis2 <- mvrtriangle(10000, mgis2, paramMargins=pars)
mgis2

par(mfrow=c(1,1))
hist(c(params(mgis2)["linf",]), main="linf", xlab="")
hist(c(params(mgis2)["k",]), main="k", prob=TRUE, xlab="")
splom(data.frame(t(params(mgis2)@.Data)),
pch=".",par.settings=list(plot.symbol=list(pch=50, cex=1.5, col=1)))

m5<-m4
shape(m5) <- mgis2

m(m5, nao=1)
dim(m(m5, nao=1))

m(m4)

rngquant(m4)<-c(0,6)
dim(m(m4))
m(m4)

rngyear(m4)<-c(2007,2015)
m(m4)
dim(m(m4))

flq <- m(m4)
```

```
bwplot(data~factor(age)|year,
      data=flq,
      par.settings=list(plot.symbol=list(cex=0.2, col="gray50"),
                  box.umbrella=list(col="gray40"),
                  box.rectangle=list(col="gray30")),
      ylab="M", xlab="age (years)", scales=list(x=list(rot=90)))


######################################################################
#################
##                                        ##
##              Reading the XSA object              ##
##    (to get assumptions on natural mortality and maturity at age)     ##
##                                        ##
######################################################################
#################

## XSA object is ages 1 to 7
aaXSA.stk <- readFLStock("~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Stochastic a4a/Data/HKE1216.IND", no.discards=TRUE) #only commercial data
aaXSA.stk <- trim(aaXSA.stk, age=0:6)

aaXSA.idx <- readFLIndices("~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Stochastic a4a/Data/TUNEFF.DAT")
name(aaXSA.idx[[1]]) <- "MEDITS_12-16"

# Length to age

aStk <- l2a(HKE.stk, vbNorm, plusgroup=6) #
aIdx <- l2a(HKE.idx, vbNorm) #

# Intro M into the object:
```

```
#mortalidad <- trim(m(m4), age=0:6)

#aStk@m <- mortalidad
#aStk@m <- mortalidad

####

# aStk@m <- m(m4)

#aStk <- trim(aStk, age=1:6)
units(aStk)[1:17]    <- as.list(c(rep(c("tonnes","thousands","kg"),4),
                          rep("NA",2),"f",rep("NA",2)))
aStk@discards.n[]          <- 0; aStk@discards.wt[] <- 0; aStk@discards <- computeDiscards(aStk)

landings(aStk)[]<-c(3792.2,3395.5,3284.4,3444.7,2532.8,3306.1,3467.4,4415.0,4081.8)

catch(aStk)[]<-computeCatch(aStk)

## we need to check SOP correction
(catch(aStk)-landings(aStk))/landings(aStk)*100

## PROBLEM! for now assuming landings = computed catches (catch.n * catch.wt)

aStk@catch.n[aStk@catch.n==0] <- 0.001

landings(aStk)<-catch(aStk)
landings.n(aStk) <- catch.n(aStk)
landings.wt(aStk) <-catch.wt(aStk)
```

```
stock.wt(aStk) <- catch.wt(aStk)

dim(aaXSA.stk@m)
dim(aStk@m)

#aStk@m<- aaXSA.stk@m
#aStk@mat <- aaXSA.stk@mat
#aStk@m.spwn <- aaXSA.stk@m.spwn


## using same m, maturity ogive, m.spawn as in XSA assessment
my.iter = 100
for (i in 1:my.iter){
  aStk@m[,,,,,i]<- aaXSA.stk@m
  aStk@mat[,,,,,i] <- aaXSA.stk@mat
  aStk@m.spwn[,,,,,i] <- aaXSA.stk@m.spwn
  aStk@harvest.spwn[,,,,,i] <- aaXSA.stk@harvest.spwn
}


range(aStk)["minfbar"] <- 2
range(aStk)["maxfbar"] <- 4
aStk <- trim(aStk, age=1:6)


aIdx@catch.n <- aIdx@index
aIdx <- trim(aIdx, age=1:6)
aIdx@range["plusgroup"] <- 6

aIdx@index[aIdx@index==0] <- 0.001
aIdx@catch.n[aIdx@catch.n==0] <- 0.001
```

```
range(aIdx)[c("startf", "endf")] <- c(2,4)

# aStk@range["min"] <- 1


summary(aIdx)
summary(aStk)

fmod <- ~factor(age) + factor(year)
qmod <- list(~s(age, k=4))
n1mod <- ~s(age,k=5)

# Tests

fit <- a4aSCA(aStk,FLIndices(aIdx),fmodel=~factor(age) + factor(year))
out <- aStk + fit

plot(out)

res <- FLQuants("Yield(t)" =landings(out),
        "Fbar(1-3)" = fbar(out),
        "R(age 1)" = R <- stock.n(out)[1,,,,],
        "SSB(t)" = ssb(out))

res

ggsave("retro.png",last_plot())

###### Choose the final model and save it

plot(out)
```

```
ggsave("final.png",last_plot())

fbar(out)
quantSums(stock.n(out)*stock.wt(out))
ssb(out)
rec(out)
harvest(out)

#-------------------------------------------------------
# Y/R
#-------------------------------------------------------
library(FLBRP)

#BRP
yprec <- brp(FLBRP(out))
yprec
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash

plot(ypr(yprec)~fbar(yprec),type='l')

plot(yprec)
ggsave("YPR.png",last_plot())

save(HKE.stk,HKE.idx, out, fit, aStk,aIdx,file="a4aoutputs.RData")

load("a4aoutputs.RData")
```

4.- Short Term Forecasting

XSA

```
# short_term_forecast.R
# Copyright 2013 Finlay Scott and Chato Osio
```

```
# Maintainer: Finlay Scott, JRC, finlay.scott@jrc.ec.europa.eu
# This program is free software; you can redistribute it and/or modify
# it under the terms of the GNU General Public License as published by
# the Free Software Foundation; either version 2 of the License, or
# (at your option) any later version.
#
# This program is distributed in the hope that it will be useful,
# but WITHOUT ANY WARRANTY; without even the implied warranty of
# MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the
# GNU General Public License for more details.
#
# You should have received a copy of the GNU General Public License
along
# with this program; if not, write to the Free Software Foundation,
Inc.,
# 51 Franklin Street, Fifth Floor, Boston, MA 02110-1301 USA.

#-----------------------------------------------------------------------
-----

# Generic script for running short-term forecasts (STF).
# This script assumes that have already run your assessment and that you
have a fully specified age-structured FLStock object

#-----------------------------------------------------------------------

# Example data set - use your own
# You need a full specified FLStock object
# Here I'm loading a dummy stock object
# load("../data/stk.RData")
# Load your own data, probably using the load() function

# Quick check that the stock object is correct
summary(aa.stk4)
plot(aa.stk4)

# For the STF we would like to run a F0.1 scenario
# Use FLBRP to get F0.1
stk_brp <- brp(FLBRP(aa.stk4))
refpts(stk_brp)
f01 <- c(refpts(stk_brp)["f0.1","harvest"])

##### f01 estimated with NOAA
# Is this number sensible?

# We also need F status quo - the geometric mean of the last X years
# Here we use 3 years
no_stk_years <- dim(rec(aa.stk4))[2]
no_fbar_years <- 3 # Or set your own as appropriate
fbars <- fbar(aa.stk4)[,(no_stk_years - no_fbar_years + 1):no_stk_years]
fbar_status_quo <- exp(mean(log(c(fbars))))
# fbar_status_quo <- c(fbar(aa.stk4)[,ac(2013)])
#-----------------------------------------------------------------------
-----
# STF
# Here we run the STF for 3 years, 2013, 2014, 2015
# You can change these as appropriate
# The first year of the STF should be the next one after the final year
in your stock data
```

```
# For example, the final year in the dummy stk object is 2012 so the
first year of the STF is 2013
stf_years <- c(2016,2017,2018)
no_stf_years <- length(stf_years)

# Set up the future stock object.
# Here we use the default assumptions about what happens to weights,
maturity and selection pattern in the future
# (e.g. weights are means of the last 3 years)
# NOTE: You may want to change some of these assumptions by hand
# See the help page for stf: ?stf for more details
stf_stk <- stf(aa.stk4, nyears = no_stf_years, wts.nyears = 3)

# Set up future recruitment to be mean of last X years
# Here we set as geometric mean of the last 3 years
no_rec_years <- 3 # Change number of years as appropriate
recs <- rec(aa.stk4)[,(no_stk_years - no_rec_years + 1):no_stk_years]
mean_rec <- exp(mean(log(c(recs))))

# We are going to run several F scenarios for the STF
# The scenarios are based on 'F status quo', which we calculated above
as the mean F of the last X years
# An STF is for three years - you could change this but if you do you
will have to hack the code below
# For a three year STF the F pattern is:
# year 1: fbar_status_quo
# year 2: fbar_status_quo * fbar_multiplier
# year 3: fbar_status_quo * fbar_multiplier
# The fbar_multiplier is the same for years 2 and 3

# We are going to run several STFs with different values for the
fbar_multiplier
# The fbar_multiplier ranges from 0.1 to 2 by 0.1
fbar_multiplier <- seq(from = 0, to = 2, by = 0.1)

# We are going to build a data.frame that builds these scenarios
# Each column in the dataframe is a year
# Each row is a scenario
# Set up the fbar scenarios - note that if you project for more than 3
years you will need to add more columns / years to the matrix
fbar_scenarios <- cbind(rep(fbar_status_quo,length(fbar_multiplier)),
                        fbar_multiplier*fbar_status_quo,
                        fbar_multiplier*fbar_status_quo)
# Add the F0.1 scenario as a final scenario
fbar_scenarios <- rbind(fbar_scenarios, c(fbar_status_quo,f01,f01))

# There are various results we want to extract from the STF
# Make an empty matrix in which to store the results
stf_results <- matrix(NA,nrow = nrow(fbar_scenarios),ncol = 10)
# Change the column names to reflect years
colnames(stf_results)                                              <-
c('Ffactor','Fbar','Catch_2015','Catch_2016','Catch_2017','Catch_2018'
,'SSB_2017','SSB_2018','Change_SSB_2017-2018(%)','Change_Catch_2015-
2016(%)')

# Store the FLStock each time
stk_stf <- FLStocks()
# Loop over the scenarios
for (scenario in 1:nrow(fbar_scenarios)) {
  cat("Scenario: ", scenario, "\n")
```

```
  # Make a target object withe F values for that scenario
  ctrl_target <- data.frame(year = stf_years,
                            quantity = "f",
                            val = fbar_scenarios[scenario,])
  # Set the control object - year, quantity and value for the moment
  ctrl_f <- fwdControl(ctrl_target)
  # Run the forward projection. We include an additional argument, maxF.
  # By default the value of maxF is 2.0
  # Here we increase it to 10.0 so that F is not limited
  stk_stf_fwd <- fwd(stf_stk, ctrl = ctrl_f, sr = list(model="mean",
params=FLPar(a = mean_rec)), maxF = 10.0)
  ## Check it has worked - uncomment out to check scenario by scenario
  #plot(stk_stf_fwd)
  # Store the result - if you want to, comment out if unnecessary
  stk_stf[[as.character(scenario)]] <- stk_stf_fwd

  # Fill results table
  stf_results[scenario,1]     <-     fbar_scenarios[scenario,2]     /
fbar_scenarios[scenario,1] # fbar status quo ratio
  stf_results[scenario,2] <- fbar(stk_stf_fwd)[,ac(2018)] # final stf
year
  stf_results[scenario,3] <- catch(stk_stf_fwd)[,ac(2015)] # last 'true'
year
  stf_results[scenario,4] <- catch(stk_stf_fwd)[,ac(2016)] # 1st stf
year
  stf_results[scenario,5] <- catch(stk_stf_fwd)[,ac(2017)] # 2nd stf
year
  stf_results[scenario,6] <- catch(stk_stf_fwd)[,ac(2018)] # final stf
year
  stf_results[scenario,7] <- ssb(stk_stf_fwd)[,ac(2017)] # 2nd stf year
  stf_results[scenario,8] <- ssb(stk_stf_fwd)[,ac(2018)] # final stf
year
  # Change in SSB
  stf_results[scenario,9]      <-      (ssb(stk_stf_fwd)[,ac(2018)]-
ssb(stk_stf_fwd)[,ac(2017)])/ssb(stk_stf_fwd)[,ac(2017)]*100 # change
in ssb in last two stf years
  stf_results[scenario,10]     <-     (catch(stk_stf_fwd)[,ac(2017)]-
catch(stk_stf_fwd)[,ac(2015)])/catch(stk_stf_fwd)[,ac(2015)]*100     #
change in catch from true year, to 2nd to last stf year
}

# Look at the table of results
View(stf_results)
# export this if necessary
write.csv(stf_results, file="stf_results_fr.csv")

# Plotting
# Plotting is not necessary for the report but here is a crude one anyway
plot(window(stk_stf, start=2008, end=2018))

ggsave("stf.png",last_plot())
```

Deterministic a4a

```
#------------------------------------------------
# a4a Short Term Forecast
#------------------------------------------------

# short_term_forecast.R
# Copyright 2013 Finlay Scott and Chato Osio
# Maintainer: Finlay Scott, JRC, finlay.scott@jrc.ec.europa.eu
# This program is free software; you can redistribute it and/or modify
# it under the terms of the GNU General Public License as published by
# the Free Software Foundation; either version 2 of the License, or
# (at your option) any later version.
#
# This program is distributed in the hope that it will be useful,
# but WITHOUT ANY WARRANTY; without even the implied warranty of
# MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the
# GNU General Public License for more details.
#
# You should have received a copy of the GNU General Public License along
# with this program; if not, write to the Free Software Foundation, Inc.,
# 51 Franklin Street, Fifth Floor, Boston, MA 02110-1301 USA.

#--------------------------------------------------------------------------

# Generic script for running short-term forecasts (STF).
# This script assumes that have already run your assessment and that you have a fully specified age-structured FLStock object

#------------------------------------------------------------------

aa.stk4 <- stk1
```

```
# Example data set - use your own
# You need a full specified FLStock object
# Here I'm loading a dummy stock object
# load("../data/stk.RData")
# Load your own data, probably using the load() function

# Quick check that the stock object is correct
summary(aa.stk4)
plot(aa.stk4)

# For the STF we would like to run a F0.1 scenario
# Use FLBRP to get F0.1
stk_brp <- brp(FLBRP(aa.stk4))
refpts(stk_brp)
f01 <- c(refpts(stk_brp)["f0.1","harvest"])

##### f01 estimated with NOAA
f01 <- 0.18
# Is this number sensible?

# We also need F status quo - the geometric mean of the last X years
# Here we use 3 years
no_stk_years <- dim(rec(aa.stk4))[2]
no_fbar_years <- 3 # Or set your own as appropriate
fbars <- fbar(aa.stk4)[,(no_stk_years - no_fbar_years + 1):no_stk_years]
fbar_status_quo <- exp(mean(log(c(fbars))))
# fbar_status_quo <- c(fbar(aa.stk4)[,ac(2013)])
#-----------------------------------------------------------------------
# STF
# Here we run the STF for 3 years, 2013, 2014, 2015
# You can change these as appropriate
```

The first year of the STF should be the next one after the final year in your stock data

For example, the final year in the dummy stk object is 2012 so the first year of the STF is 2013

stf_years <- c(2016,2017,2018)

no_stf_years <- length(stf_years)

Set up the future stock object.

Here we use the default assumptions about what happens to weights, maturity and selection pattern in the future

(e.g. weights are means of the last 3 years)

NOTE: You may want to change some of these assumptions by hand

See the help page for stf: ?stf for more details

stf_stk <- stf(aa.stk4, nyears = no_stf_years, wts.nyears = 3)

Set up future recruitment to be mean of last X years

Here we set as geometric mean of the last 3 years

no_rec_years <- 3 # Change number of years as appropriate

recs <- rec(aa.stk4)[,(no_stk_years - no_rec_years + 1):no_stk_years]

mean_rec <- exp(mean(log(c(recs))))

We are going to run several F scenarios for the STF

The scenarios are based on 'F status quo', which we calculated above as the mean F of the last X years

An STF is for three years - you could change this but if you do you will have to hack the code below

For a three year STF the F pattern is:

year 1: fbar_status_quo

year 2: fbar_status_quo * fbar_multiplier

year 3: fbar_status_quo * fbar_multiplier

The fbar_multiplier is the same for years 2 and 3

We are going to run several STFs with different values for the fbar_multiplier

The fbar_multiplier ranges from 0.1 to 2 by 0.1

```
fbar_multiplier <- seq(from = 0, to = 2, by = 0.1)

# We are going to build a data.frame that builds these scenarios
# Each column in the dataframe is a year
# Each row is a scenario
# Set up the fbar scenarios - note that if you project for more than 3 years you will need to add more columns / years to the matrix
fbar_scenarios <- cbind(rep(fbar_status_quo,length(fbar_multiplier)),
                        fbar_multiplier*fbar_status_quo,
                        fbar_multiplier*fbar_status_quo)
# Add the F0.1 scenario as a final scenario
fbar_scenarios <- rbind(fbar_scenarios, c(fbar_status_quo,f01,f01))

# There are various results we want to extract from the STF
# Make an empty matrix in which to store the results
stf_results <- matrix(NA,nrow = nrow(fbar_scenarios),ncol = 10)
# Change the column names to reflect years
colnames(stf_results) <- c('Ffactor','Fbar','Catch_2015','Catch_2016','Catch_2017','Catch_2018','SSB_2017','SSB_2018','Change_SSB_2017-2018(%)','Change_Catch_2015-2016(%)')

# Store the FLStock each time
stk_stf <- FLStocks()
# Loop over the scenarios
for (scenario in 1:nrow(fbar_scenarios)) {
  cat("Scenario: ", scenario, "\n")
  # Make a target object withe F values for that scenario
  ctrl_target <- data.frame(year = stf_years,
                            quantity = "f",
                            val = fbar_scenarios[scenario,])
  # Set the control object - year, quantity and value for the moment
  ctrl_f <- fwdControl(ctrl_target)
  # Run the forward projection. We include an additional argument, maxF.
```

```
# By default the value of maxF is 2.0
# Here we increase it to 10.0 so that F is not limited
stk_stf_fwd <- fwd(stf_stk, ctrl = ctrl_f, sr = list(model="mean", params=FLPar(a = mean_rec)), maxF = 10.0)
## Check it has worked - uncomment out to check scenario by scenario
#plot(stk_stf_fwd)
# Store the result - if you want to, comment out if unnecessary
stk_stf[[as.character(scenario)]] <- stk_stf_fwd

# Fill results table
stf_results[scenario,1] <- fbar_scenarios[scenario,2] / fbar_scenarios[scenario,1] # fbar status quo ratio
stf_results[scenario,2] <- fbar(stk_stf_fwd)[,ac(2018)] # final stf year
stf_results[scenario,3] <- catch(stk_stf_fwd)[,ac(2015)] # last 'true' year
stf_results[scenario,4] <- catch(stk_stf_fwd)[,ac(2016)] # 1st stf year
stf_results[scenario,5] <- catch(stk_stf_fwd)[,ac(2017)] # 2nd stf year
stf_results[scenario,6] <- catch(stk_stf_fwd)[,ac(2018)] # final stf year
stf_results[scenario,7] <- ssb(stk_stf_fwd)[,ac(2017)] # 2nd stf year
stf_results[scenario,8] <- ssb(stk_stf_fwd)[,ac(2018)] # final stf year
# Change in SSB
stf_results[scenario,9] <- (ssb(stk_stf_fwd)[,ac(2018)]-ssb(stk_stf_fwd)[,ac(2017)])/ssb(stk_stf_fwd)[,ac(2017)]*100 # change in ssb in last two stf years
stf_results[scenario,10] <- (catch(stk_stf_fwd)[,ac(2017)]-catch(stk_stf_fwd)[,ac(2015)])/catch(stk_stf_fwd)[,ac(2015)]*100 # change in catch from true year, to 2nd to last stf year
}

# Look at the table of results
View(stf_results)
# export this if necessary
write.csv(stf_results, file="stf_results_fr.csv")

# Plotting
```

```
# Plotting is not necessary for the report but here is a crude one anyway
plot(window(stk_stf, start=2008, end=2018))

ggsave("stf.png",last_plot())
```

5.- Long/Medium Term Forecasting

XSA

```
##################################################
###                                            ###
###         MSE - 50% Reduction (Final)        ###
###            XSA - deterministic             ###
##################################################

rm(list=ls())

library(FLa4a)
library(FLash)
library(FLAssess)
library(ggplotFL)
library(FLBRP)
library(FLSAM)
library(FLCore)
library(FLEDA)
library(FLXSA)
library(SQLiteFL)
library(doBy)
library(reshape)
library(devtools)
library(msy)

setwd("C:/Users/edusa/Google
Drive/Rprojects/MSE/2017/StraitOfSicily/HKE/XSA/Data")

source('C:/Users/edusa/Google
Drive/Rprojects/MSE/2017/StraitOfSicily/HKE/XSA/Scripts/MSE_funs2017.R
')

load("C:/Users/edusa/Google
Drive/Rprojects/MSE/2017/StraitOfSicily/HKE/XSA/Data/stk&idxready.rda"
)

aa.stk <- HKE.stk
aa.idx <- HKE.idx

#FSE 1
FLXSA.control.aa4   <-   FLXSA.control(x=NULL,   tol=1e-09,   maxit=30,
min.nse=0.3, fse=1,
                                   rage=0,      qage=1,      shk.n=TRUE,
shk.f=TRUE, shk.yrs=3, shk.ages=3,
                                   window=100,  tsrange=20,  tspower=3,
vpa=FALSE)

aa.xsa4 <- FLXSA(aa.stk, aa.idx, FLXSA.control.aa4)
aa.stk4 <- aa.stk+aa.xsa4
plot(aa.stk4)

fit <- aa.xsa4

stk1 <- aa.stk4
stk <- stk1
```

```
ids <- HKE.idx
ids <- FLIndices(HKE.idx)

ids[[1]]@index[ids[[1]]@index == 0] <- 0.1
ids[[1]]@catch.n[ids[[1]]@catch.n == 0] <- 0.1

plot(stk1) #Good One

ref.points<-brp(FLBRP(stk1))

#============================================================
#BRP
#============================================================
#======================================================================
=========
# Stochastic projections to show example of envelope analysis
#----------------------------------------------------------------------
---------
# Fcurr: 0.8271455
# Btrig: 5331.954
# Bpa: 5331.954
# Blim: 2665.977
# Fmsy: 0.4


nit <- 250                              # iterations - should be 250
it <- 250
y0 <- range(stk)["minyear"]     # year zero (initial) = 1975
ny <- 24                              # number of years to project -
Usually 20
# In order for this code to run iy = dy
dy <- 2015                            # data year
ay <- 2015                            # assessment year
iy <- 2015                           # initial projections year (also
intermediate)
fy <- iy + ny -1                      # final year
vy <- ac(iy:fy)
nsqy <- 3                             # number of SQ years upon which
to average results

mny <- 2020                           #2016 # min year to get to trg
mxy <- 2020                           # 2016 # max year to get to trg

trgy <- 2015

yprec <- brp(FLBRP(stk))
yprec
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash

plot(ypr(yprec)~fbar(yprec),type='l')

# 1. F status quo: maintain F from 2015
fsq <- mean(c(fbar(stk)[,ac(dy)]))
plot(yprec)
ggsave("YPR.png",last_plot())
fcurr <- mean(harvest(stk)[,3])
blim <- min(ssb(stk))
bpa <- blim*2
```

```
Btrig <- bpa
#idx0 <- idx
dt <- date()
idx <- ids

# Fill in zeros with small values
catch.n(stk)[catch.n(stk)==0] <- 0.01
for (i in 1:length(idx)){
  index(idx[[i]])[index(idx[[i]])==0] <- 0.01
}

# Expand the objects to the number of iterations
# - stock
stk <- propagate(stk, fill.iter=T, iter=nit)
# introduce variability in the catch numbers at age
stk@catch.n  <-  stk@catch.n  *  exp(rlnorm(  prod(dim(stk@catch.n)),  0,
0.2))
stk@catch <- quantSums(catch.n(stk)*catch.wt(stk))
# - index
for (i in 1:length(idx))
  idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=nit)
# Or using XSA - set own control
for (it in 1:nit)
  stk[,,,,,it] <- stk[,,,,,it] + FLXSA(stk[,,,,,it], iter(idx[[1]],it),
FLXSA.control.aa4)

#============================================================
# S/R
#============================================================

sr <- fmle(as.FLSR(stk, model="segreg")) # bevholt, ricker
sr.res <- residuals(sr)
plot(sr.res)
plot(sr)
a <- as.numeric(sr@params["a"])
b <- as.numeric(sr@params["b"])
rec.res <- residuals(sr)
set.seed(108)
# mean
arima.fit <- arima(an(rec.res), order = c(1, 0, 0))
# create autocorrelation in residuals and propagate throughout stock
into the future
# from initial year of projections (iy) to last of projections (ny-1)
sr.res <- make.arma.resid(arima.fit, age = 0, years = iy:(iy + ny-1),
nit = it)
plot(sr.res)

#============================================================
#
#============================================================

TAC <- FLQuant(NA, dimnames=list(TAC="all", year=vy, iter=1:it))
BB <- FLQuant(0, dimnames=list(TAC="all", year=vy, iter=1:it))

# # # Prepare stock objects we need, with iterations and propagate
towards final year
# stk <- iter(ids, 1)
# # simulate new stock ased on a4a final fit
# sstk <- stk + simulate(fit, it)
# stk <- iter(aa.stk, 1)
```

```
# sstk <- stk + simulate(fit, it)

summary(sstk)
plot(sstk)

# sstk<-stk
# summary(sstk)
# plot(sstk)
# # short term forecast: start with a projection of F into the future
to ny (16 yrs)
# # this serves as a starting point for projecting the stock

pstk <- stf(stk, ny, 3, 3)            # harvest is average last 3 years

landings.n(pstk) <- propagate(landings.n(pstk), it)
discards.n(pstk) <- propagate(discards.n(pstk), it)

#
ipy <- (iy+1):range(pstk)["maxyear"]
ly.pos <- (dims(pstk)$year-24+1):dims(pstk)$year

idx <- ids

for (i in 1:length(idx)){
  idx.q <- idx_temp <- FLQuant(NA, dimnames=dimnames(stock.n(pstk)))
  for (it in 1:nit) {
    lst <- mcf(list(idx[[i]]@index, stock.n(stk)))
    idx.lq <- iter(log(lst[[1]]/lst[[2]]),it)
    idx.lq[is.infinite(idx.lq)] <- NA # fix zeros
    idx.qmu <- idx.qsig <- stock.n(iter(pstk,1))
    idx.qmu[] <- yearMeans(idx.lq)
    idx.qsig[] <- log((sqrt(yearVars(idx.lq))/yearMeans(idx.lq))^2 + 1)
    idx.q[,ac(y0:dy),,,,it] <- exp(idx.lq[,ac(y0:dy),])
    for (yy in vy)
      idx.q[,yy,,,,it] <- rlnorm(1, idx.qmu[,yy,], idx.qsig[,yy,])
  }
  plot(idx.q)
  idx_temp <- idx.q * stock.n(pstk)
  idx[[i]] <- FLIndex(index=idx_temp, index.q=idx.q)
  range(idx[[i]])[c("startf", "endf")] <- c(0, 0)
  plot(index(idx[[i]]))
}



#---------------------------------------------------------------------
---------
# 1a. (1a) STATUS QUO SCENARIO - SEGMENTED STOCK RECRUITMENT WITH BPT
AT MEAN SSB
#---------------------------------------------------------------------
---------

# Set up the Btrigger (in this case halfway between Blim and Bpa)
Btrig <- bpa
idx0 <- idx
dt <- date()


####################################
for(i in vy[-length(vy)]){
```

```
  ## i <- vy[-length(vy)][1]
  print(i)
  gc()
  ay <- an(i)   # an is equivalent to as.numeric
  cat(i, "\n")
  vy0 <- 1:(ay-y0) # data years (positions vector)
  sqy <- (ay-y0-nsqy+1):(ay-y0) # status quo years (positions vector)
  stk0 <- pstk[,vy0]
  catch.n(stk0) <- catch.n(stk0) + 1 # avoid zeros
  ## note that vy0 is changing below so index is being updated
  for (index_counter in 1:length(idx)){
    idx0[[index_counter]] <- idx[[index_counter]][,vy0]
    index(idx[[index_counter]])[,i]                              <-
stock.n(pstk)[,i]*index.q(idx[[index_counter]])[,i] + 1
  }
  ##
  fit0 <- FLXSA(stk0, idx0, FLXSA.control.aa4)
  stock.n(stk0) <- stock.n(fit0)
  harvest(stk0) <- harvest(fit0)
  # fwd control
  fsq0 <- yearMeans(fbar(stk0)[,c(sqy)])
  dnms <- list(iter=1:it, year=c(ay, ay + 1), c("min", "val", "max"))
  arr0 <- array(NA, dimnames=dnms, dim=unlist(lapply(dnms, length)))
  ## ftrg.vec <- rep(ftrg, it) ## original
  #refpt <- data.frame(ssb = 1, harvest = 1)
  #ftrg.q <- hcr.nocheck.GFCM.f(ssb(stk0)[, ac(an(i) - 1)], Fsq0=fsq0,
refpt = refpt, Btrig = Btrig, Fmin = 0, Blim = blim, Bpa=bpa)
  #ftrg.q <- hcr.nocheck(ssb(stk0)[, ac(an(i) - 1)], refpt = refpt, Ftar
= ftrg, Btrig = bpa, Fmin = 0, Blim = blim)
  #ftrg.vec <- an(ftrg.q)
  #Bescape <- blim
  ftrg.q <- fbar(stk1)[,"2015",,,,] * 0.5
  ftrg.vec <- rep(an(ftrg.q),it)
  arr0[,,"val"] <- c(fsq0, ftrg.vec) #rep(NA, it)
  arr0[,,"min"] <- c(rep(NA, 2 * it))
  arr0 <- aperm(arr0, c(2,3,1))
  ctrl <- fwdControl(data.frame(year=c(ay, ay+1), quantity=c('f', 'f'),
val=NA))
  ctrl@trgtArray <- arr0
  #future_catch <- c(catch(stk0)[,"2013"]) * 0.9
  #ctrl_catch  <-  fwdControl(data.frame(year=an(ay:(ay+1)),  quantity  =
"catch", val=future_catch))
  #ctrl_target <- ctrl_target[order(ctrl_target$year),]
  #ctrl <- fwdControl(ctrl_catch)
  #ctrl   <-   fwdControl(data.frame(year=c(ay,   ay+1,   ay   +   3),
quantity=c('f', 'f', 'ssb'), val=NA))
  #ctrl@trgtArray <- arr0
  ##
  stkTmp <- stf(stk0, 2)
  stkTmp   <-   fwd(stkTmp,   ctrl=ctrl,   sr=sr,   sr.residuals   =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE
  ## USING F
  TAC[,ac(ay+1)] <- catch(stkTmp)[,ac(ay+1)]
  # OM proj
  ctrl@target <- ctrl@target[2,]
  ## original was catch
  ##ctrl@target[,"quantity"] <- "catch"
  ctrl@trgtArray <- ctrl@trgtArray[2,,,drop=FALSE]
```

```
  ## original was catch
  ##ctrl@trgtArray[,"val",] <- c(TAC[,ac(ay+1)]) #+ BB[,ac(ay)])
  pstk    <-    fwd(pstk,    ctrl=ctrl,    sr=sr,    sr.residuals    =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay+1)]), sr.residuals.mult = TRUE
  #BB[,ac(ay+1)]        <-        iterMedians(TAC[,ac(ay+1)])        -
catch(pstk)[,ac(ay+1)]
}

nstk <-pstk

plot(window(nstk, end=2037))

save(nstk, file='results_no_sel.RData')

savePlot( file='HAKEstatusquoscenario.jpeg', type='jpeg')
# Ignore final year - not used
# Look at distribution of SSB in final year - 1 (assume projection has
stabilised)
ssb(pstk)[,"2024"]
hist(ssb(pstk)[,"2024"])

# Proportion below Blim - are you less than 5%
sum(ssb(pstk)[,"2030"] < blim) / nit

#########################################################
##################################################
###                                            ###
###         MSE - 50% Reduction (Final)        ###
###           a4a - deterministic              ###
##################################################

rm(list=ls())
cat("\014")
#

library(FLa4a)
library(FLash)
library(FLAssess)
library(ggplotFL)
library(FLBRP)
library(FLSAM)
library(FLCore)
library(FLEDA)
library(FLXSA)
library(SQLiteFL)
library(doBy)
library(reshape)
library(devtools)
library(msy)

setwd("~/MSE      Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data")

source('~/MSE     Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Scripts/MSE_funs2017.R')

load("~/MSE       Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data/stk&amp;idxready.rda")
```

```
aa.stk <- HKE.stk
aa.idx <- HKE.idx
idx <- HKE.idx


HKE.stk <- setPlusGroup(HKE.stk, 7)

plot(HKE.stk)

# model fitting:
qmod1 <- list(~ factor(age),~ factor(age) )
fmod2 <- ~ factor(age) + s(year, k=4)
srmod1 <- ~ factor(year)

# fit1 <- a4aSCA(stock = HKE.stk, indices = HKE.idx,fmodel=fmod1,
qmodel=qmod1, srmodel=srmod1)
# fit1 <- a4aSCA(stock = HKE.stk, indices = HKE.idx,fmodel=fmod2,
qmodel=qmod1, srmodel=srmod1) #BetterOne
fit <- a4aSCA(stock = aa.stk, indices = (HKE.idx),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1,verbose = FALSE, fit =
"assessment")

stk1 <- aa.stk + fit

ids <- HKE.idx
ids <- FLIndices(HKE.idx)

stk <-stk1
ids[[1]]@index[ids[[1]]@index == 0] <- 0.1
ids[[1]]@catch.n[ids[[1]]@catch.n == 0] <- 0.1

plot(stk1) #Good One

ref.points<-brp(FLBRP(stk1))

#==========================================================
#BRP
#==========================================================
#====================================================================
=========
# Stochastic projections to show example of envelope analysis
#--------------------------------------------------------------------
---------
# Fcurr: 0.8271455
# Btrig: 5331.954
# Bpa: 5331.954
# Blim: 2665.977
# Fmsy: 0.4

# Assign names to tuning indices

it <- 10                                # iterations - should be 250
nit <- 10
y0 <- range(stk)["minyear"]         # year zero (initial) = 1975
ny <- 24                                 # number of years to project -
Usually 20
# In order for this code to run iy = dy
dy <- 2015                              # data year
ay <- 2015                              # assessment year
```

```
iy <- 2015                              # initial projections year (also
intermediate)
fy <- iy + ny -1                         # final year
vy <- ac(iy:fy)
nsqy <- 3                                # number of SQ years upon which
to average results

mny <- 2020                              #2016 # min year to get to trg
mxy <- 2020                              # 2016 # max year to get to trg

# Management quantities
#flo <- 0.23
#fup <- 0.36
#fmsy <- 0.55
# 1. F status quo: maintain F from 2015
yprec <- brp(FLBRP(stk))
yprec
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash
plot(ypr(yprec)~fbar(yprec),type='l')
fsq <- mean(c(fbar(stk1)[,ac(dy)]))
plot(yprec)
ggsave("YPR.png",last_plot())
fcurr <- mean(harvest(stk)[,3])
blim <- min(ssb(stk1))
bpa <- blim*2
Btrig <- bpa
idx0 <- idx
dt <- date()

# Fill in zeros with small values
catch.n(stk)[catch.n(stk)==0] <- 0.01
for (i in 1:length(idx)){
  index(idx[[i]])[index(idx[[i]])==0] <- 0.01
}

# Expand the objects to the number of iterations
stk <- propagate(stk, fill.iter=T, iter=nit)
# introduce variability in the catch numbers at age
stk@catch.n  <-  stk@catch.n  *  exp(rlnorm(  prod(dim(stk@catch.n)),  0,
0.2))
stk@catch <- quantSums(catch.n(stk)*catch.wt(stk))
# - index
for (i in 1:length(idx))
  idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=nit)

#--------------------------------------------------------------------------
---------
# S/R
#--------------------------------------------------------------------------
---------

# sr <- fmle(as.FLSR(sstk, model="geomean"))
sr <- fmle(as.FLSR(stk, model="segreg"), fixed=list(b=mean(ssb(stk))))
# method="L-BFGS-B"mean(ssb(stk))
sr.res <- residuals(sr)
plot(sr.res)
plot(sr)
a <- as.numeric(sr@params["a"])
b <- as.numeric(sr@params["b"])
```

```
rec.res <- residuals(sr)
set.seed(108)
# mean
arima.fit <- arima(an(rec.res), order = c(1, 0, 0))
# create autocorrelation in residuals and propagate throughout stock
into the future
# from initial year of projections (iy) to last of projections (ny-1)
sr.res <- make.arma.resid(arima.fit, age = 0, years = iy:(iy + ny-1),
nit = it)
plot(sr.res)


#----------------------------------------------------------------------
----------
#
#----------------------------------------------------------------------
----------

# Fixed objects
TAC <- FLQuant(NA, dimnames=list(TAC="all", year=vy, iter=1:it))
BB <- FLQuant(0, dimnames=list(TAC="all", year=vy, iter=1:it))

# # Prepare stock objects we need, with iterations and propagate towards
final year
stk <- iter(aa.stk, 1)
# simulate new stock ased on a4a final fit
sstk <- stk + simulate(fit, it)

summary(sstk)
plot(sstk)

# short term forecast: start with a projection of F into the future to
ny (16 yrs)
# this serves as a starting point for projecting the stock

pstk <- stf(sstk, ny, 3, 3)              # harvest is average last 3
years

landings.n(pstk) <- propagate(landings.n(pstk), it)
discards.n(pstk) <- propagate(discards.n(pstk), it)

ipy <- (iy+1):range(pstk)["maxyear"]
ly.pos <- (dims(pstk)$year-24+1):dims(pstk)$year

# idx<- ids

# for (i in 1:length(idx))
#   idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=it)

idx <- ids

for (i in 1:length(idx)){
  idx.q <- idx_temp <- FLQuant(NA, dimnames=dimnames(stock.n(pstk)))
  for (it in 1:it) {
    lst <- mcf(list(idx[[i]]@index, stock.n(stk)))
    idx.lq <- iter(log(lst[[1]]/lst[[2]]),it)
    idx.lq[is.infinite(idx.lq)] <- NA # fix zeros
    idx.qmu <- idx.qsig <- stock.n(iter(pstk,1))
    idx.qmu[] <- yearMeans(idx.lq)
    idx.qsig[] <- log((sqrt(yearVars(idx.lq))/yearMeans(idx.lq))^2 + 1)
```

```
    idx.q[,ac(y0:dy),,,,it] <- exp(idx.lq[,ac(y0:dy),])
    for (yy in vy)
      idx.q[,yy,,,,it] <- rlnorm(1, idx.qmu[,yy,], idx.qsig[,yy,])
  }
  plot(idx.q)
  idx_temp <- idx.q * stock.n(pstk)
  idx[[i]] <- FLIndex(index=idx_temp, index.q=idx.q)
  range(idx[[i]])[c("startf", "endf")] <- c(0, 0)
  plot(index(idx[[i]]))
}


#----------------------------------------------------------------------
---------
# 70% Reduction on F
#----------------------------------------------------------------------
---------

# Set up the Btrigger (in this case Bpa)
Btrig <- bpa
idx0 <- idx
dt <- date()

#########################################################
# go fish
for(i in vy[-length(vy)]){
  ## i <- vy[-length(vy)][1]
  print(i)
  gc()
  ay <- an(i)   # an is equivalent to as.numeric
  cat(i, "\n")
  vy0 <- 1:(ay-y0) # data years (positions vector)
  sqy <- (ay-y0-nsqy+1):(ay-y0) # status quo years (positions vector)
  stk0 <- pstk[,vy0]
  catch.n(stk0) <- catch.n(stk0) + 1 # avoid zeros
  ## note that vy0 is changing below so index is being updated
  for (index_counter in 1:length(idx)){
    idx0[[index_counter]] <- idx[[index_counter]][,vy0]
    index(idx[[index_counter]])[,i]                          <-
stock.n(pstk)[,i]*index.q(idx[[index_counter]])[,i] + 1
  }
  ##
  qmod1 <- list(~ factor(age),~ factor(age) )
  fmod2 <- ~ factor(age) + s(year, k=4)
  srmod1 <- ~ factor(year)
  fit          <-            sca(stk0,            FLIndices(idx0),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1)
  stk0 <- stk0 + fit
  # fwd control
  fsq0 <- yearMeans(fbar(stk0)[,c(sqy)])
  dnms <- list(iter=1:it, year=c(ay, ay + 1), c("min", "val", "max"))
  arr0 <- array(NA, dimnames=dnms, dim=unlist(lapply(dnms, length)))
  ## ftrg.vec <- rep(ftrg, it) ## original
  #refpt <- data.frame(ssb = 1, harvest = 1)
  #ftrg.q <- hcr.nocheck.GFCM.f(ssb(stk0)[, ac(an(i) - 1)], Fsq0=fsq0,
refpt = refpt, Btrig = Btrig, Fmin = 0, Blim = blim, Bpa=bpa)
  #ftrg.q <- hcr.nocheck(ssb(stk0)[, ac(an(i) - 1)], refpt = refpt, Ftar
= ftrg, Btrig = bpa, Fmin = 0, Blim = blim)
  #ftrg.vec <- an(ftrg.q)
  #Bescape <- blim
```

```
  ftrg.q <- fbar(stk1)[,"2015",,,,] * 0.3
  ftrg.vec <- rep(an(ftrg.q),it)
  arr0[,,"val"] <- c(fsq0, ftrg.vec) #rep(NA, it)
  arr0[,,"min"] <- c(rep(NA, 2 * it))
  arr0 <- aperm(arr0, c(2,3,1))
  ctrl <- fwdControl(data.frame(year=c(ay, ay+1), quantity=c('f', 'f'),
val=NA))
  ctrl@trgtArray <- arr0
  #future_catch <- c(catch(stk0)[,"2013"]) * 0.9
  #ctrl_catch  <-  fwdControl(data.frame(year=an(ay:(ay+1)),  quantity  =
"catch", val=future_catch))
  #ctrl_target <- ctrl_target[order(ctrl_target$year),]
  #ctrl <- fwdControl(ctrl_catch)
  #ctrl   <-   fwdControl(data.frame(year=c(ay,   ay+1,   ay   +   3),
quantity=c('f', 'f', 'ssb'), val=NA))
  #ctrl@trgtArray <- arr0
  ##
  stkTmp <- stf(stk0, 2)
  stkTmp   <-   fwd(stkTmp,   ctrl=ctrl,   sr=sr,   sr.residuals   =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE
  ## USING F
  TAC[,ac(ay+1)] <- catch(stkTmp)[,ac(ay+1)]
  # OM proj
  ctrl@target <- ctrl@target[2,]
  ## original was catch
  ##ctrl@target[,"quantity"] <- "catch"
  ctrl@trgtArray <- ctrl@trgtArray[2,,,drop=FALSE]
  ## original was catch
  ##ctrl@trgtArray[,"val",] <- c(TAC[,ac(ay+1)]) #+ BB[,ac(ay)])
  pstk   <-   fwd(pstk,   ctrl=ctrl,   sr=sr,   sr.residuals   =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay+1)]), sr.residuals.mult = TRUE
  #BB[,ac(ay+1)]       <-       iterMedians(TAC[,ac(ay+1)])       -
catch(pstk)[,ac(ay+1)]
}

return(val)
date()

nstk <- pstk

plot(window(nstk, end=2037))
ssb(pstk)[,"2024"]
hist(ssb(pstk)[,"2024"])

# Proportion below Blim - are you less than 5%
sum(ssb(pstk)[,"2030"] < blim) / it

####################################################
###                                              ###
###         MSE - 90% Reduction (Final)          ###
###           a4a - deterministic                ###
####################################################

rm(list=ls())
cat("\014")
#
```

```
library(FLa4a)
library(FLash)
library(FLAssess)
library(ggplotFL)
library(FLBRP)
library(FLSAM)
library(FLCore)
library(FLEDA)
library(FLXSA)
library(SQLiteFL)
library(doBy)
library(reshape)
library(devtools)
library(msy)

setwd("~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic a4a/Data")

source('~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic a4a/Scripts/MSE_funs2017.R')

load("~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic a4a/Data/stk&amp;idxready.rda")

aa.stk <- HKE.stk
aa.idx <- HKE.idx
idx <- HKE.idx


HKE.stk <- setPlusGroup(HKE.stk, 7)

plot(HKE.stk)

# model fitting:
qmod1 <- list(~ factor(age),~ factor(age) )
fmod2 <- ~ factor(age) + s(year, k=4)
srmod1 <- ~ factor(year)

# fit1 <- a4aSCA(stock = HKE.stk, indices = HKE.idx,fmodel=fmod1, qmodel=qmod1, srmodel=srmod1)
# fit1 <- a4aSCA(stock = HKE.stk, indices = HKE.idx,fmodel=fmod2, qmodel=qmod1, srmodel=srmod1) #BetterOne
fit <- a4aSCA(stock = aa.stk, indices = (HKE.idx), fmodel=fmod2,qmodel=qmod1,srmodel=srmod1,verbose = FALSE, fit = "assessment")

stk1 <- aa.stk + fit

ids <- HKE.idx
ids <- FLIndices(HKE.idx)

stk <-stk1
ids[[1]]@index[ids[[1]]@index == 0] <- 0.1
ids[[1]]@catch.n[ids[[1]]@catch.n == 0] <- 0.1

plot(stk1) #Good One

ref.points<-brp(FLBRP(stk1))
```

```
#==========================================================
#BRP
#==========================================================
#====================================================================
=========
# Stochastic projections to show example of envelope analysis
#--------------------------------------------------------------------
---------
# Fcurr: 0.8271455
# Btrig: 5331.954
# Bpa: 5331.954
# Blim: 2665.977
# Fmsy: 0.4

# Assign names to tuning indices

it <- 10                               # iterations - should be 250
nit <- 10
y0 <- range(stk)["minyear"]        # year zero (initial) = 1975
ny <- 24                                # number of years to project -
Usually 20
# In order for this code to run iy = dy
dy <- 2015                             # data year
ay <- 2015                             # assessment year
iy <- 2015                            # initial projections year (also
intermediate)
fy <- iy + ny -1                       # final year
vy <- ac(iy:fy)
nsqy <- 3                              # number of SQ years upon which
to average results

mny <- 2020                            #2016 # min year to get to trg
mxy <- 2020                            # 2016 # max year to get to trg

# Management quantities
#flo <- 0.23
#fup <- 0.36
#fmsy <- 0.55
# 1. F status quo: maintain F from 2015
yprec <- brp(FLBRP(stk))
yprec
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash
plot(ypr(yprec)~fbar(yprec),type='l')
fsq <- mean(c(fbar(stk1)[,ac(dy)]))
plot(yprec)
ggsave("YPR.png",last_plot())
fcurr <- mean(harvest(stk)[,3])
blim <- min(ssb(stk1))
bpa <- blim*2
Btrig <- bpa
idx0 <- idx
dt <- date()

# Fill in zeros with small values
catch.n(stk)[catch.n(stk)==0] <- 0.01
for (i in 1:length(idx)){
  index(idx[[i]])[index(idx[[i]])==0] <- 0.01
}
```

```
# Expand the objects to the number of iterations
stk <- propagate(stk, fill.iter=T, iter=nit)
# introduce variability in the catch numbers at age
stk@catch.n <- stk@catch.n * exp(rlnorm( prod(dim(stk@catch.n)), 0,
0.2))
stk@catch <- quantSums(catch.n(stk)*catch.wt(stk))
# - index
for (i in 1:length(idx))
  idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=nit)

#-----------------------------------------------------------------------
---------
# S/R
#-----------------------------------------------------------------------
---------

# sr <- fmle(as.FLSR(sstk, model="geomean"))
sr <- fmle(as.FLSR(stk, model="segreg"), fixed=list(b=mean(ssb(stk))))
# method="L-BFGS-B"mean(ssb(stk))
sr.res <- residuals(sr)
plot(sr.res)
plot(sr)
a <- as.numeric(sr@params["a"])
b <- as.numeric(sr@params["b"])
rec.res <- residuals(sr)
set.seed(108)
# mean
arima.fit <- arima(an(rec.res), order = c(1, 0, 0))
# create autocorrelation in residuals and propagate throughout stock
into the future
# from initial year of projections (iy) to last of projections (ny-1)
sr.res <- make.arma.resid(arima.fit, age = 0, years = iy:(iy + ny-1),
nit = it)
plot(sr.res)


#-----------------------------------------------------------------------
----------
#
#-----------------------------------------------------------------------
----------

# Fixed objects
TAC <- FLQuant(NA, dimnames=list(TAC="all", year=vy, iter=1:it))
BB <- FLQuant(0, dimnames=list(TAC="all", year=vy, iter=1:it))

# # Prepare stock objects we need, with iterations and propagate towards
final year
stk <- iter(aa.stk, 1)
# simulate new stock ased on a4a final fit
sstk <- stk + simulate(fit, it)

summary(sstk)
plot(sstk)

# short term forecast: start with a projection of F into the future to
ny (16 yrs)
# this serves as a starting point for projecting the stock
```

```
pstk <- stf(sstk, ny, 3, 3)              # harvest is average last 3
years

landings.n(pstk) <- propagate(landings.n(pstk), it)
discards.n(pstk) <- propagate(discards.n(pstk), it)

ipy <- (iy+1):range(pstk)["maxyear"]
ly.pos <- (dims(pstk)$year-24+1):dims(pstk)$year

# idx<- ids

# for (i in 1:length(idx))
#   idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=it)

idx <- ids

for (i in 1:length(idx)){
  idx.q <- idx_temp <- FLQuant(NA, dimnames=dimnames(stock.n(pstk)))
  for (it in 1:it) {
    lst <- mcf(list(idx[[i]]@index, stock.n(stk)))
    idx.lq <- iter(log(lst[[1]]/lst[[2]]),it)
    idx.lq[is.infinite(idx.lq)] <- NA # fix zeros
    idx.qmu <- idx.qsig <- stock.n(iter(pstk,1))
    idx.qmu[] <- yearMeans(idx.lq)
    idx.qsig[] <- log((sqrt(yearVars(idx.lq))/yearMeans(idx.lq))^2 + 1)
    idx.q[,ac(y0:dy),,,,it] <- exp(idx.lq[,ac(y0:dy),])
    for (yy in vy)
      idx.q[,yy,,,,it] <- rlnorm(1, idx.qmu[,yy,], idx.qsig[,yy,])
  }
  plot(idx.q)
  idx_temp <- idx.q * stock.n(pstk)
  idx[[i]] <- FLIndex(index=idx_temp, index.q=idx.q)
  range(idx[[i]])[c("startf", "endf")] <- c(0, 0)
  plot(index(idx[[i]]))
}


#-----------------------------------------------------------------------
---------
# 70% Reduction
#-----------------------------------------------------------------------
---------

# Set up the Btrigger (in this case Bpa)
Btrig <- bpa
idx0 <- idx
dt <- date()

##########################################################
# go fish
for(i in vy[-length(vy)]){
  ## i <- vy[-length(vy)][1]
  print(i)
  gc()
  ay <- an(i)   # an is equivalent to as.numeric
  cat(i, "\n")
  vy0 <- 1:(ay-y0) # data years (positions vector)
  sqy <- (ay-y0-nsqy+1):(ay-y0) # status quo years (positions vector)
  stk0 <- pstk[,vy0]
  catch.n(stk0) <- catch.n(stk0) + 1 # avoid zeros
```

```
  ## note that vy0 is changing below so index is being updated
  for (index_counter in 1:length(idx)){
    idx0[[index_counter]] <- idx[[index_counter]][,vy0]
    index(idx[[index_counter]])[,i]                              <-
stock.n(pstk)[,i]*index.q(idx[[index_counter]])[,i] + 1
  }
  ##
  qmod1 <- list(~ factor(age),~ factor(age) )
  fmod2 <- ~ factor(age) + s(year, k=4)
  srmod1 <- ~ factor(year)
  fit             <-             sca(stk0,            FLIndices(idx0),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1)
  stk0 <- stk0 + fit
  # fwd control
  fsq0 <- yearMeans(fbar(stk0)[,c(sqy)])
  dnms <- list(iter=1:it, year=c(ay, ay + 1), c("min", "val", "max"))
  arr0 <- array(NA, dimnames=dnms, dim=unlist(lapply(dnms, length)))
  ## ftrg.vec <- rep(ftrg, it) ## original
  #refpt <- data.frame(ssb = 1, harvest = 1)
  #ftrg.q <- hcr.nocheck.GFCM.f(ssb(stk0)[, ac(an(i) - 1)], Fsq0=fsq0,
refpt = refpt, Btrig = Btrig, Fmin = 0, Blim = blim, Bpa=bpa)
  #ftrg.q <- hcr.nocheck(ssb(stk0)[, ac(an(i) - 1)], refpt = refpt, Ftar
= ftrg, Btrig = bpa, Fmin = 0, Blim = blim)
  #ftrg.vec <- an(ftrg.q)
  #Bescape <- blim
  ftrg.q <- fbar(stk1)[,"2015",,,,] * 0.1
  ftrg.vec <- rep(an(ftrg.q),it)
  arr0[,,"val"] <- c(fsq0, ftrg.vec) #rep(NA, it)
  arr0[,,"min"] <- c(rep(NA, 2 * it))
  arr0 <- aperm(arr0, c(2,3,1))
  ctrl <- fwdControl(data.frame(year=c(ay, ay+1), quantity=c('f', 'f'),
val=NA))
  ctrl@trgtArray <- arr0
  #future_catch <- c(catch(stk0)[,"2013"]) * 0.9
  #ctrl_catch  <-  fwdControl(data.frame(year=an(ay:(ay+1)),  quantity  =
"catch", val=future_catch))
  #ctrl_target <- ctrl_target[order(ctrl_target$year),]
  #ctrl <- fwdControl(ctrl_catch)
  #ctrl   <-   fwdControl(data.frame(year=c(ay,   ay+1,   ay   +   3),
quantity=c('f', 'f', 'ssb'), val=NA))
  #ctrl@trgtArray <- arr0
  ##
  stkTmp <- stf(stk0, 2)
  stkTmp   <-   fwd(stkTmp,   ctrl=ctrl,   sr=sr,   sr.residuals   =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE
  ## USING F
  TAC[,ac(ay+1)] <- catch(stkTmp)[,ac(ay+1)]
  # OM proj
  ctrl@target <- ctrl@target[2,]
  ## original was catch
  ##ctrl@target[,"quantity"] <- "catch"
  ctrl@trgtArray <- ctrl@trgtArray[2,,,drop=FALSE]
  ## original was catch
  ##ctrl@trgtArray[,"val",] <- c(TAC[,ac(ay+1)]) #+ BB[,ac(ay)])
  pstk    <-    fwd(pstk,    ctrl=ctrl,    sr=sr,    sr.residuals    =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay+1)]), sr.residuals.mult = TRUE
```

```
  #BB[,ac(ay+1)]        <-        iterMedians(TAC[,ac(ay+1)])        -
catch(pstk)[,ac(ay+1)]
}

return(val)
date()

nstk <- pstk

plot(window(nstk, end=2037))
ssb(pstk)[,"2024"]
hist(ssb(pstk)[,"2024"])

# Proportion below Blim - are you less than 5%
sum(ssb(pstk)[,"2030"] < blim) / it

##################################################
###                                            ###
###         MSE -      FMSY                    ###
###           a4a - deterministic              ###
##################################################


rm(list=ls())
cat("\014")
#

library(FLa4a)
library(FLash)
library(FLAssess)
library(ggplotFL)
library(FLBRP)
library(FLSAM)
library(FLCore)
library(FLEDA)
library(FLXSA)
library(SQLiteFL)
library(doBy)
library(reshape)
library(devtools)
library(msy)

setwd("~/MSE      Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data")

source('~/MSE     Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Scripts/MSE_funs2017.R')

load("~/MSE       Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data/stk&amp;idxready.rda")

aa.stk <- HKE.stk
aa.idx <- HKE.idx
idx <- HKE.idx


HKE.stk <- setPlusGroup(HKE.stk, 7)

plot(HKE.stk)
```

```
# model fitting:
qmod1 <- list(~ factor(age),~ factor(age) )
fmod2 <- ~ factor(age) + s(year, k=4)
srmod1 <- ~ factor(year)

# fit1 <- a4aSCA(stock = HKE.stk, indices = HKE.idx,fmodel=fmod1,
qmodel=qmod1, srmodel=srmod1)
# fit1 <- a4aSCA(stock = HKE.stk, indices = HKE.idx,fmodel=fmod2,
qmodel=qmod1, srmodel=srmod1) #BetterOne
fit <- a4aSCA(stock = aa.stk, indices = (HKE.idx),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1,verbose = FALSE, fit =
"assessment")

stk1 <- aa.stk + fit

ids <- HKE.idx
ids <- FLIndices(HKE.idx)

stk <-stk1
ids[[1]]@index[ids[[1]]@index == 0] <- 0.1
ids[[1]]@catch.n[ids[[1]]@catch.n == 0] <- 0.1

plot(stk1) #Good One

ref.points<-brp(FLBRP(stk1))

#===========================================================
#BRP
#===========================================================
#===================================================================
=========
# Stochastic projections to show example of envelope analysis
#-------------------------------------------------------------------
---------
# Fcurr: 0.8271455
# Btrig: 5331.954
# Bpa: 5331.954
# Blim: 2665.977
# Fmsy: 0.4

# Assign names to tuning indices

it <- 10                               # iterations - should be 250
nit <- 10
y0 <- range(stk)["minyear"]         # year zero (initial) = 1975
ny <- 24                                # number of years to project -
Usually 20
# In order for this code to run iy = dy
dy <- 2015                             # data year
ay <- 2015                             # assessment year
iy <- 2015                            # initial projections year (also
intermediate)
fy <- iy + ny -1                       # final year
vy <- ac(iy:fy)
nsqy <- 3                              # number of SQ years upon which
to average results

mny <- 2020                            #2016 # min year to get to trg
mxy <- 2020                            # 2016 # max year to get to trg
```

```
# Management quantities
#flo <- 0.23
#fup <- 0.36
#fmsy <- 0.55
# 1. F status quo: maintain F from 2015
yprec <- brp(FLBRP(stk))
yprec
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash
plot(ypr(yprec)~fbar(yprec),type='l')
fsq <- mean(c(fbar(stk1)[,ac(dy)]))
plot(yprec)
ggsave("YPR.png",last_plot())
fcurr <- mean(harvest(stk)[,3])
blim <- min(ssb(stk1))
bpa <- blim*2
Btrig <- bpa
idx0 <- idx
dt <- date()

# Fill in zeros with small values
catch.n(stk)[catch.n(stk)==0] <- 0.01
for (i in 1:length(idx)){
  index(idx[[i]])[index(idx[[i]])==0] <- 0.01
}

# Expand the objects to the number of iterations
stk <- propagate(stk, fill.iter=T, iter=nit)
# introduce variability in the catch numbers at age
stk@catch.n  <-  stk@catch.n  *  exp(rlnorm(  prod(dim(stk@catch.n)),  0,
0.2))
stk@catch <- quantSums(catch.n(stk)*catch.wt(stk))
# - index
for (i in 1:length(idx))
  idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=nit)

#----------------------------------------------------------------------
---------
# S/R
#----------------------------------------------------------------------
---------

# sr <- fmle(as.FLSR(sstk, model="geomean"))
sr <- fmle(as.FLSR(stk, model="segreg"), fixed=list(b=mean(ssb(stk))))
# method="L-BFGS-B"mean(ssb(stk))
sr.res <- residuals(sr)
plot(sr.res)
plot(sr)
a <- as.numeric(sr@params["a"])
b <- as.numeric(sr@params["b"])
rec.res <- residuals(sr)
set.seed(108)
# mean
arima.fit <- arima(an(rec.res), order = c(1, 0, 0))
# create autocorrelation in residuals and propagate throughout stock
into the future
# from initial year of projections (iy) to last of projections (ny-1)
sr.res <- make.arma.resid(arima.fit, age = 0, years = iy:(iy + ny-1),
nit = it)
plot(sr.res)
```

```
#----------------------------------------------------------------------
----------
#
#----------------------------------------------------------------------
----------

# Fixed objects
TAC <- FLQuant(NA, dimnames=list(TAC="all", year=vy, iter=1:it))
BB <- FLQuant(0, dimnames=list(TAC="all", year=vy, iter=1:it))

# # Prepare stock objects we need, with iterations and propagate towards
final year
stk <- iter(aa.stk, 1)
# simulate new stock ased on a4a final fit
sstk <- stk + simulate(fit, it)

summary(sstk)
plot(sstk)

# short term forecast: start with a projection of F into the future to
ny (16 yrs)
# this serves as a starting point for projecting the stock

pstk <- stf(sstk, ny, 3, 3)              # harvest is average last 3
years

landings.n(pstk) <- propagate(landings.n(pstk), it)
discards.n(pstk) <- propagate(discards.n(pstk), it)

ipy <- (iy+1):range(pstk)["maxyear"]
ly.pos <- (dims(pstk)$year-24+1):dims(pstk)$year

# idx<- ids

# for (i in 1:length(idx))
#   idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=it)

idx <- ids

for (i in 1:length(idx)){
  idx.q <- idx_temp <- FLQuant(NA, dimnames=dimnames(stock.n(pstk)))
  for (it in 1:it) {
    lst <- mcf(list(idx[[i]]@index, stock.n(stk)))
    idx.lq <- iter(log(lst[[1]]/lst[[2]]),it)
    idx.lq[is.infinite(idx.lq)] <- NA # fix zeros
    idx.qmu <- idx.qsig <- stock.n(iter(pstk,1))
    idx.qmu[] <- yearMeans(idx.lq)
    idx.qsig[] <- log((sqrt(yearVars(idx.lq))/yearMeans(idx.lq))^2 + 1)
    idx.q[,ac(y0:dy),,,,it] <- exp(idx.lq[,ac(y0:dy),])
    for (yy in vy)
      idx.q[,yy,,,,it] <- rlnorm(1, idx.qmu[,yy,], idx.qsig[,yy,])
  }
  plot(idx.q)
  idx_temp <- idx.q * stock.n(pstk)
  idx[[i]] <- FLIndex(index=idx_temp, index.q=idx.q)
  range(idx[[i]])[c("startf", "endf")] <- c(0, 0)
  plot(index(idx[[i]]))
}
```

```
#----------------------------------------------------------------------
---------
# 2d. (5d) SCENARIO GFCM REGULATION 2013 Halfway Blim-Bpa = Btrigger -
USING F INCREASING LINEARLY WHEN B >
# AND WHEN F < 0.53 (with and without Bescape)
# bkpt max SSB reduced time series
#----------------------------------------------------------------------
---------

# Set up the Btrigger (in this case Bpa)
Btrig <- bpa
idx0 <- idx
dt <- date()

#########################################################
# go fish
for(i in vy[-length(vy)]){
  ## i <- vy[-length(vy)][1]
  print(i)
  gc()
  ay <- an(i)   # an is equivalent to as.numeric
  cat(i, "\n")
  vy0 <- 1:(ay-y0) # data years (positions vector)
  sqy <- (ay-y0-nsqy+1):(ay-y0) # status quo years (positions vector)
  stk0 <- pstk[,vy0]
  catch.n(stk0) <- catch.n(stk0) + 1 # avoid zeros
  ## note that vy0 is changing below so index is being updated
  for (index_counter in 1:length(idx)){
    idx0[[index_counter]] <- idx[[index_counter]][,vy0]
    index(idx[[index_counter]])[,i]                              <-
stock.n(pstk)[,i]*index.q(idx[[index_counter]])[,i] + 1
  }
  ##
  qmod1 <- list(~ factor(age),~ factor(age) )
  fmod2 <- ~ factor(age) + s(year, k=4)
  srmod1 <- ~ factor(year)
  fit             <-             sca(stk0,             FLIndices(idx0),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1)
  stk0 <- stk0 + fit
  # fwd control
  fsq0 <- yearMeans(fbar(stk0)[,c(sqy)])
  dnms <- list(iter=1:it, year=c(ay, ay + 1), c("min", "val", "max"))
  arr0 <- array(NA, dimnames=dnms, dim=unlist(lapply(dnms, length)))
  ## ftrg.vec <- rep(ftrg, it) ## original
  #refpt <- data.frame(ssb = 1, harvest = 1)
  #ftrg.q <- hcr.nocheck.GFCM.f(ssb(stk0)[, ac(an(i) - 1)], Fsq0=fsq0,
refpt = refpt, Btrig = Btrig, Fmin = 0, Blim = blim, Bpa=bpa)
  #ftrg.q <- hcr.nocheck(ssb(stk0)[, ac(an(i) - 1)], refpt = refpt, Ftar
= ftrg, Btrig = bpa, Fmin = 0, Blim = blim)
  #ftrg.vec <- an(ftrg.q)
  #Bescape <- blim
  ftrg.q <- fbar(stk1)[,"2015",,,,]/4.875 #fbar/F0.1
  ftrg.vec <- rep(an(ftrg.q),it)
  arr0[,,"val"] <- c(fsq0, ftrg.vec) #rep(NA, it)
  arr0[,,"min"] <- c(rep(NA, 2 * it))
  arr0 <- aperm(arr0, c(2,3,1))
  ctrl <- fwdControl(data.frame(year=c(ay, ay+1), quantity=c('f', 'f'),
val=NA))
```

```
  ctrl@trgtArray <- arr0
  #future_catch <- c(catch(stk0)[,"2013"]) * 0.9
  #ctrl_catch  <-  fwdControl(data.frame(year=an(ay:(ay+1)),  quantity  =
"catch", val=future_catch))
  #ctrl_target <- ctrl_target[order(ctrl_target$year),]
  #ctrl <- fwdControl(ctrl_catch)
  #ctrl   <-   fwdControl(data.frame(year=c(ay,   ay+1,   ay   +   3),
quantity=c('f', 'f', 'ssb'), val=NA))
  #ctrl@trgtArray <- arr0
  ##
  stkTmp <- stf(stk0, 2)
  stkTmp   <-   fwd(stkTmp,   ctrl=ctrl,   sr=sr,   sr.residuals   =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE
  ## USING F
  TAC[,ac(ay+1)] <- catch(stkTmp)[,ac(ay+1)]
  # OM proj
  ctrl@target <- ctrl@target[2,]
  ## original was catch
  ##ctrl@target[,"quantity"] <- "catch"
  ctrl@trgtArray <- ctrl@trgtArray[2,,,drop=FALSE]
  ## original was catch
  ##ctrl@trgtArray[,"val",] <- c(TAC[,ac(ay+1)]) #+ BB[,ac(ay)])
  pstk   <-   fwd(pstk,   ctrl=ctrl,   sr=sr,   sr.residuals   =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay+1)]), sr.residuals.mult = TRUE
  #BB[,ac(ay+1)]        <-        iterMedians(TAC[,ac(ay+1)])        -
catch(pstk)[,ac(ay+1)]
}

return(val)
date()

nstk <- pstk

plot(window(nstk, end=2037))
ssb(pstk)[,"2024"]
hist(ssb(pstk)[,"2024"])

# Proportion below Blim - are you less than 5%
sum(ssb(pstk)[,"2030"] < blim) / it
```

Deterministic a4a

```
#######################################################################
########################
########
########
########                               Full  Thesis  Script  -  Together
########
########            4 Scenarios- Status Quo, 50%F Red, 70%F Red, Red.
to                ########
########                                                      31/05/2017
########
########
########
#######################################################################
########################

#######################################################################
########################
#######################################################################
########################
# Status Quo
#######################################################################
########################
#######################################################################
########################

rm(list=ls())
cat("\014")
#

library(FLa4a)
library(FLash)
library(FLAssess)
library(ggplotFL)
library(FLBRP)
library(FLSAM)
library(FLCore)
library(FLEDA)
library(FLXSA)
library(SQLiteFL)
library(doBy)
library(reshape)
library(devtools)
library(msy)

setwd("~/MSE      Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data")

source('~/MSE     Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Scripts/MSE_funs2017.R')

load("~/MSE       Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data/stk&amp;idxready.rda")

aa.stk <- HKE.stk
aa.idx <- HKE.idx
idx <- HKE.idx
```

```
HKE.stk <- setPlusGroup(HKE.stk, 7)

# plot(HKE.stk)

# model fitting:
qmod1 <- list(~ factor(age),~ factor(age) )
fmod2 <- ~ factor(age) + s(year, k=4)
srmod1 <- ~ factor(year)

fit <- a4aSCA(stock = aa.stk, indices = (HKE.idx),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1,verbose = FALSE, fit =
"assessment")

stk1 <- aa.stk + fit

ids <- HKE.idx
ids <- FLIndices(HKE.idx)

stk <-stk1
ids[[1]]@index[ids[[1]]@index == 0] <- 0.1
ids[[1]]@catch.n[ids[[1]]@catch.n == 0] <- 0.1

# plot(stk1) #Good One

ref.points<-brp(FLBRP(stk1))




# Assign names to tuning indices

it <- 250                                # iterations - should be 250
nit <- 250
y0 <- range(stk)["minyear"]          # year zero (initial) = 1975
ny <- 24                                 # number of years to project -
Usually 20
# In order for this code to run iy = dy
dy <- 2015                              # data year
ay <- 2015                              # assessment year
iy <- 2015                             # initial projections year (also
intermediate)
fy <- iy + ny -1                        # final year
vy <- ac(iy:fy)
nsqy <- 3                               # number of SQ years upon which
to average results

mny <- 2020                             #2016 # min year to get to trg
mxy <- 2020                             # 2016 # max year to get to trg

# Management quantities
#flo <- 0.23
#fup <- 0.36
#fmsy <- 0.55
# 1. F status quo: maintain F from 2015
yprec <- brp(FLBRP(stk))
yprec
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash
```

```
plot(ypr(yprec)~fbar(yprec),type='l')
fsq <- mean(c(fbar(stk1)[,ac(dy)]))
# plot(yprec)
ggsave("YPR.png",last_plot())
fcurr <- mean(harvest(stk)[,3])
blim <- min(ssb(stk1))
bpa <- blim*2
Btrig <- bpa
idx0 <- idx
dt <- date()

# Fill in zeros with small values
catch.n(stk)[catch.n(stk)==0] <- 0.01
for (i in 1:length(idx)){
  index(idx[[i]])[index(idx[[i]])==0] <- 0.01
}

# Expand the objects to the number of iterations
stk <- propagate(stk, fill.iter=T, iter=nit)
# introduce variability in the catch numbers at age
stk@catch.n  <-  stk@catch.n  *  exp(rlnorm(  prod(dim(stk@catch.n)),  0,
0.2))
stk@catch <- quantSums(catch.n(stk)*catch.wt(stk))
# - index
for (i in 1:length(idx))
  idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=nit)

#-----------------------------------------------------------------------
---------
# S/R
#-----------------------------------------------------------------------
---------

# sr <- fmle(as.FLSR(sstk, model="geomean"))
sr <- fmle(as.FLSR(stk, model="segreg"), fixed=list(b=mean(ssb(stk))))
# method="L-BFGS-B"mean(ssb(stk))
sr.res <- residuals(sr)
# plot(sr.res)
plot(sr)
a <- as.numeric(sr@params["a"])
b <- as.numeric(sr@params["b"])
rec.res <- residuals(sr)
set.seed(108)
# mean
arima.fit <- arima(an(rec.res), order = c(1, 0, 0))
# create autocorrelation in residuals and propagate throughout stock
into the future
# from initial year of projections (iy) to last of projections (ny-1)
sr.res <- make.arma.resid(arima.fit, age = 0, years = iy:(iy + ny-1),
nit = it)
# plot(sr.res)


#-----------------------------------------------------------------------
----------
#
#-----------------------------------------------------------------------
----------

# Fixed objects
```

```
TAC <- FLQuant(NA, dimnames=list(TAC="all", year=vy, iter=1:it))
BB <- FLQuant(0, dimnames=list(TAC="all", year=vy, iter=1:it))

# # Prepare stock objects we need, with iterations and propagate towards
final year
stk <- iter(aa.stk, 1)
# simulate new stock ased on a4a final fit
sstk <- stk + simulate(fit, it)

summary(sstk)
plot(sstk)

# short term forecast: start with a projection of F into the future to
ny (16 yrs)
# this serves as a starting point for projecting the stock

pstk <- stf(sstk, ny, 3, 3)              # harvest is average last 3
years

landings.n(pstk) <- propagate(landings.n(pstk), it)
discards.n(pstk) <- propagate(discards.n(pstk), it)

ipy <- (iy+1):range(pstk)["maxyear"]
ly.pos <- (dims(pstk)$year-24+1):dims(pstk)$year

# idx<- ids

# for (i in 1:length(idx))
#   idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=it)

idx <- ids

for (i in 1:length(idx)){
  idx.q <- idx_temp <- FLQuant(NA, dimnames=dimnames(stock.n(pstk)))
  for (it in 1:it) {
    lst <- mcf(list(idx[[i]]@index, stock.n(stk)))
    idx.lq <- iter(log(lst[[1]]/lst[[2]]),it)
    idx.lq[is.infinite(idx.lq)] <- NA # fix zeros
    idx.qmu <- idx.qsig <- stock.n(iter(pstk,1))
    idx.qmu[] <- yearMeans(idx.lq)
    idx.qsig[] <- log((sqrt(yearVars(idx.lq))/yearMeans(idx.lq))^2 + 1)
    idx.q[,ac(y0:dy),,,,it] <- exp(idx.lq[,ac(y0:dy),])
    for (yy in vy)
      idx.q[,yy,,,,it] <- rlnorm(1, idx.qmu[,yy,], idx.qsig[,yy,])
  }
  plot(idx.q)
  idx_temp <- idx.q * stock.n(pstk)
  idx[[i]] <- FLIndex(index=idx_temp, index.q=idx.q)
  range(idx[[i]])[c("startf", "endf")] <- c(0, 0)
  plot(index(idx[[i]]))
}


blim <- min(ssb(stk))
bpa <- blim*2
Btrig <- blim+((bpa-blim)/2)
idx0 <- idx
dt <- date()

# Set up the Btrigger (in this case Bpa)
```

```
Btrig <- bpa
idx0 <- idx
dt <- date()


for(i in vy[-length(vy)]){   #a[-(15:16)]
  ## i <- vy[-length(vy)][1]
  print(i)
  gc()
  ay <- an(i)   # an is equivalent to as.numeric
  cat(i, ">")
  vy0 <- 1:(ay-y0) # data years (positions vector)
  sqy <- (ay-y0-nsqy+1):(ay-y0) # status quo years (positions vector)
  #sqy <- (ay-y0-nsqy+1):(ay-y0)
  # define stock0 from pstk until the last populated year
  # pstk is at the beginning only populated into the future fro F
  # the rest is only 1975-2015 but as the loop progresses through the
projection
  # years the object is populated with projected numbers
  stk0 <- pstk[,vy0]
  # add 1 to everything to avoid zeros
  catch.n(stk0) <- catch.n(stk0) + 1 # avoid zeros
  ## note that vy0 is changing below so index is being updated
  for (index_counter in 1:length(idx)){
    idx0[[index_counter]] <- idx[[index_counter]][,vy0]
    index(idx[[index_counter]])[,i]                                   <-
stock.n(pstk)[,i]*index.q(idx[[index_counter]])[,i] + 1
  }
  ##
  # qmod5 <- list(~s(age, k=5) + s(year, k=4), ~s(age, k=5) + s(year,
k=4))
  # fmod8 <- ~ s(age, k = 5) + s(year, k=18) + te(age, year, k = c(4,5))
  # rmodel4 <- ~ s(year, k=20)
  #  fit  <-  sca(stk0,  FLIndices(idx0),  fmodel=fmod8,  srmodel=rmodel4,
qmodel=qmod5)
  # stk0 <- stk0 + fit
  qmod1 <- list(~ factor(age),~ factor(age) )
  fmod2 <- ~ factor(age) + s(year, k=4)
  srmod1 <- ~ factor(year)
  fit             <-             sca(stk0,             FLIndices(idx0),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1)

  # fwd control
  # what is F status quo? is it fixed or does it vary as you progress
in the projection?
  fsq0 <- fsq # status quo 2013-2015 from SAM (deterministic)
  dnms <- list(iter=1:it, year=c(ay, ay + 1), c("min", "val", "max"))
  arr0 <- array(NA, dimnames=dnms, dim=unlist(lapply(dnms, length)))
  ## ftrg.vec <- rep(ftrg, it) ## original
  refpt <- data.frame(harvest = 1)
  ftrg.vec <- an(fsq0) # Ftarget = status quo
  #Bescape <- blim
  arr0[,,"val"] <- c(fsq0, ftrg.vec)
  #arr0[,,"min"] <- c(rep(NA, 2 * it), rep(Bescape, it))
  #arr0 <- aperm(arr0, c(2,3,1))
  # in Control you define what you want to vary in ay and ay+1 (which
is F)
  ctrl <- fwdControl(data.frame(year=c(ay, ay+1), quantity=c('f', 'f'),
val=NA))
  ctrl@trgtArray <- arr0
```

```
  ## Short term forecast of stk0
  stkTmp <- stf(stk0, 2)
  # project forward with the control you want and the SR rel you defined
above, with residuals
  stkTmp    <-    fwd(stkTmp,    ctrl=ctrl,    sr=sr,    sr.residuals    =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #
  TAC[,ac(ay+1)] <- catch(stkTmp)[,ac(ay+1)]
  # OM proj
  ctrl@target <- ctrl@target[2,]
  ctrl@trgtArray <- ctrl@trgtArray[2,,,drop=FALSE]
  # update pstk with stkTmp
  pstk    <-    fwd(pstk,    ctrl=ctrl,    sr=sr,    sr.residuals    =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #
}

return(val)
date()

nstk <- pstk

plot(window(nstk, end=2037))
return(val)
date()

######################################################################
#########################
######################################################################
#########################
# 50% F Reduction Scenario
######################################################################
#########################
######################################################################
#########################

##################################################
###                                            ###
###         MSE - 50% Reduction (Final)        ###
###           a4a - deterministic              ###
##################################################

rm(list=ls())
cat("\014")
#

library(FLa4a)
library(FLash)
library(FLAssess)
library(ggplotFL)
library(FLBRP)
library(FLSAM)
library(FLCore)
library(FLEDA)
library(FLXSA)
library(SQLiteFL)
library(doBy)
library(reshape)
library(devtools)
library(msy)
```

```
setwd("~/MSE      Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data")

source('~/MSE     Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Scripts/MSE_funs2017.R')

load("~/MSE       Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data/stk&amp;idxready.rda")

aa.stk <- HKE.stk
aa.idx <- HKE.idx
idx <- HKE.idx


HKE.stk <- setPlusGroup(HKE.stk, 7)
# plot(HKE.stk)

# model fitting:
qmod1 <- list(~ factor(age),~ factor(age) )
fmod2 <- ~ factor(age) + s(year, k=4)
srmod1 <- ~ factor(year)

#  fit1  <-  a4aSCA(stock  =  HKE.stk,  indices  =  HKE.idx,fmodel=fmod1,
qmodel=qmod1, srmodel=srmod1)
#  fit1  <-  a4aSCA(stock  =  HKE.stk,  indices  =  HKE.idx,fmodel=fmod2,
qmodel=qmod1, srmodel=srmod1) #BetterOne
fit    <-    a4aSCA(stock    =    aa.stk,    indices    =    (HKE.idx),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1,verbose   =   FALSE,   fit   =
"assessment")

stk1 <- aa.stk + fit

ids <- HKE.idx
ids <- FLIndices(HKE.idx)

stk <-stk1
ids[[1]]@index[ids[[1]]@index == 0] <- 0.1
ids[[1]]@catch.n[ids[[1]]@catch.n == 0] <- 0.1

# plot(stk1) #Good One

ref.points<-brp(FLBRP(stk1))


#===========================================================
#BRP
#===========================================================
#=====================================================================
=========
# Stochastic projections to show example of envelope analysis
#---------------------------------------------------------------------
---------
# Fcurr: 0.8271455
# Btrig: 5331.954
# Bpa: 5331.954
# Blim: 2665.977
# Fmsy: 0.4

# Assign names to tuning indices
```

```
it <- 250                                # iterations - should be 250
nit <- 250
y0 <- range(stk)["minyear"]         # year zero (initial) = 1975
ny <- 24                                 # number of years to project -
Usually 20
# In order for this code to run iy = dy
dy <- 2015                              # data year
ay <- 2015                              # assessment year
iy <- 2015                             # initial projections year (also
intermediate)
fy <- iy + ny -1                        # final year
vy <- ac(iy:fy)
nsqy <- 3                               # number of SQ years upon which
to average results

mny <- 2020                             #2016 # min year to get to trg
mxy <- 2020                             # 2016 # max year to get to trg

# Management quantities
#flo <- 0.23
#fup <- 0.36
#fmsy <- 0.55
# 1. F status quo: maintain F from 2015
yprec <- brp(FLBRP(stk))
yprec
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash
# plot(ypr(yprec)~fbar(yprec),type='l')
fsq <- mean(c(fbar(stk1)[,ac(dy)]))
# plot(yprec)
ggsave("YPR.png",last_plot())
fcurr <- mean(harvest(stk)[,3])
blim <- min(ssb(stk1))
bpa <- blim*2
Btrig <- bpa
idx0 <- idx
dt <- date()

# Fill in zeros with small values
catch.n(stk)[catch.n(stk)==0] <- 0.01
for (i in 1:length(idx)){
  index(idx[[i]])[index(idx[[i]])==0] <- 0.01
}

# Expand the objects to the number of iterations
stk <- propagate(stk, fill.iter=T, iter=nit)
# introduce variability in the catch numbers at age
stk@catch.n  <-  stk@catch.n  *  exp(rlnorm(  prod(dim(stk@catch.n)),  0,
0.2))
stk@catch <- quantSums(catch.n(stk)*catch.wt(stk))
# - index
for (i in 1:length(idx))
  idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=nit)

#----------------------------------------------------------------------
---------
# S/R
#----------------------------------------------------------------------
---------
```

```
# sr <- fmle(as.FLSR(sstk, model="geomean"))
sr <- fmle(as.FLSR(stk, model="segreg"), fixed=list(b=mean(ssb(stk))))
# method="L-BFGS-B"mean(ssb(stk))
sr.res <- residuals(sr)
# plot(sr.res)
plot(sr)
a <- as.numeric(sr@params["a"])
b <- as.numeric(sr@params["b"])
rec.res <- residuals(sr)
set.seed(108)
# mean
arima.fit <- arima(an(rec.res), order = c(1, 0, 0))
# create autocorrelation in residuals and propagate throughout stock
into the future
# from initial year of projections (iy) to last of projections (ny-1)
sr.res <- make.arma.resid(arima.fit, age = 0, years = iy:(iy + ny-1),
nit = it)
plot(sr.res)


#---------------------------------------------------------------------
----------
#
#---------------------------------------------------------------------
----------

# Fixed objects
TAC <- FLQuant(NA, dimnames=list(TAC="all", year=vy, iter=1:it))
BB <- FLQuant(0, dimnames=list(TAC="all", year=vy, iter=1:it))

# # Prepare stock objects we need, with iterations and propagate towards
final year
stk <- iter(aa.stk, 1)
# simulate new stock ased on a4a final fit
sstk <- stk + simulate(fit, it)

summary(sstk)
# plot(sstk)

# short term forecast: start with a projection of F into the future to
ny (16 yrs)
# this serves as a starting point for projecting the stock

pstk <- stf(sstk, ny, 3, 3)               # harvest is average last 3
years

landings.n(pstk) <- propagate(landings.n(pstk), it)
discards.n(pstk) <- propagate(discards.n(pstk), it)

ipy <- (iy+1):range(pstk)["maxyear"]
ly.pos <- (dims(pstk)$year-24+1):dims(pstk)$year

# idx<- ids

# for (i in 1:length(idx))
#   idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=it)

idx <- ids

for (i in 1:length(idx)){
```

```
  idx.q <- idx_temp <- FLQuant(NA, dimnames=dimnames(stock.n(pstk)))
  for (it in 1:it) {
    lst <- mcf(list(idx[[i]]@index, stock.n(stk)))
    idx.lq <- iter(log(lst[[1]]/lst[[2]]),it)
    idx.lq[is.infinite(idx.lq)] <- NA # fix zeros
    idx.qmu <- idx.qsig <- stock.n(iter(pstk,1))
    idx.qmu[] <- yearMeans(idx.lq)
    idx.qsig[] <- log((sqrt(yearVars(idx.lq))/yearMeans(idx.lq))^2 + 1)
    idx.q[,ac(y0:dy),,,,it] <- exp(idx.lq[,ac(y0:dy),])
    for (yy in vy)
      idx.q[,yy,,,,it] <- rlnorm(1, idx.qmu[,yy,], idx.qsig[,yy,])
  }
  plot(idx.q)
  idx_temp <- idx.q * stock.n(pstk)
  idx[[i]] <- FLIndex(index=idx_temp, index.q=idx.q)
  range(idx[[i]])[c("startf", "endf")] <- c(0, 0)
  plot(index(idx[[i]]))
}


#----------------------------------------------------------------------
---------
# 50% Reduction
#----------------------------------------------------------------------
---------

# Set up the Btrigger (in this case Bpa)
Btrig <- bpa
idx0 <- idx
dt <- date()

#########################################################
# go fish
for(i in vy[-length(vy)]){
  ## i <- vy[-length(vy)][1]
  print(i)
  gc()
  ay <- an(i)   # an is equivalent to as.numeric
  cat(i, "\n")
  vy0 <- 1:(ay-y0) # data years (positions vector)
  sqy <- (ay-y0-nsqy+1):(ay-y0) # status quo years (positions vector)
  stk0 <- pstk[,vy0]
  catch.n(stk0) <- catch.n(stk0) + 1 # avoid zeros
  ## note that vy0 is changing below so index is being updated
  for (index_counter in 1:length(idx)){
    idx0[[index_counter]] <- idx[[index_counter]][,vy0]
    index(idx[[index_counter]])[,i]                              <-
stock.n(pstk)[,i]*index.q(idx[[index_counter]])[,i] + 1
  }
  ##
  qmod1 <- list(~ factor(age),~ factor(age) )
  fmod2 <- ~ factor(age) + s(year, k=4)
  srmod1 <- ~ factor(year)
  fit            <-            sca(stk0,            FLIndices(idx0),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1)
  stk0 <- stk0 + fit
  # fwd control
  fsq0 <- yearMeans(fbar(stk0)[,c(sqy)])
  dnms <- list(iter=1:it, year=c(ay, ay + 1), c("min", "val", "max"))
  arr0 <- array(NA, dimnames=dnms, dim=unlist(lapply(dnms, length)))
```

```
  ## ftrg.vec <- rep(ftrg, it) ## original
  #refpt <- data.frame(ssb = 1, harvest = 1)
  #ftrg.q <- hcr.nocheck.GFCM.f(ssb(stk0)[, ac(an(i) - 1)], Fsq0=fsq0,
refpt = refpt, Btrig = Btrig, Fmin = 0, Blim = blim, Bpa=bpa)
  #ftrg.q <- hcr.nocheck(ssb(stk0)[, ac(an(i) - 1)], refpt = refpt, Ftar
= ftrg, Btrig = bpa, Fmin = 0, Blim = blim)
  #ftrg.vec <- an(ftrg.q)
  #Bescape <- blim
  ftrg.q <- fbar(stk1)[,"2015",,,,] * 0.5
  ftrg.vec <- rep(an(ftrg.q),it)
  arr0[,,"val"] <- c(fsq0, ftrg.vec) #rep(NA, it)
  arr0[,,"min"] <- c(rep(NA, 2 * it))
  arr0 <- aperm(arr0, c(2,3,1))
  ctrl <- fwdControl(data.frame(year=c(ay, ay+1), quantity=c('f', 'f'),
val=NA))
  ctrl@trgtArray <- arr0
  #future_catch <- c(catch(stk0)[,"2013"]) * 0.9
  #ctrl_catch <- fwdControl(data.frame(year=an(ay:(ay+1)), quantity =
"catch", val=future_catch))
  #ctrl_target <- ctrl_target[order(ctrl_target$year),]
  #ctrl <- fwdControl(ctrl_catch)
  #ctrl <- fwdControl(data.frame(year=c(ay, ay+1, ay + 3),
quantity=c('f', 'f', 'ssb'), val=NA))
  #ctrl@trgtArray <- arr0
  ##
  stkTmp <- stf(stk0, 2)
  stkTmp <- fwd(stkTmp, ctrl=ctrl, sr=sr, sr.residuals =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE
  ## USING F
  TAC[,ac(ay+1)] <- catch(stkTmp)[,ac(ay+1)]
  # OM proj
  ctrl@target <- ctrl@target[2,]
  ## original was catch
  ##ctrl@target[,"quantity"] <- "catch"
  ctrl@trgtArray <- ctrl@trgtArray[2,,,drop=FALSE]
  ## original was catch
  ##ctrl@trgtArray[,"val",] <- c(TAC[,ac(ay+1)]) #+ BB[,ac(ay)])
  pstk <- fwd(pstk, ctrl=ctrl, sr=sr, sr.residuals =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay+1)]), sr.residuals.mult = TRUE
  #BB[,ac(ay+1)] <- iterMedians(TAC[,ac(ay+1)]) -
catch(pstk)[,ac(ay+1)]
}

return(val)
date()

nstk <- pstk

plot(window(nstk, end=2037))
# ssb(pstk)[,"2024"]
# hist(ssb(pstk)[,"2024"])
#
# # Proportion below Blim - are you less than 5%
# sum(ssb(pstk)[,"2030"] < blim) / it
```

```
######################################################################
#########################
######################################################################
#########################
# 70% F Reduction Scenario
######################################################################
#########################
######################################################################
#########################

##################################################
###                                            ###
###         MSE - 50% Reduction (Final)        ###
###           a4a - deterministic              ###
##################################################

rm(list=ls())
cat("\014")
#

library(FLa4a)
library(FLash)
library(FLAssess)
library(ggplotFL)
library(FLBRP)
library(FLSAM)
library(FLCore)
library(FLEDA)
library(FLXSA)
library(SQLiteFL)
library(doBy)
library(reshape)
library(devtools)
library(msy)

setwd("~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data")

source('~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Scripts/MSE_funs2017.R')

load("~/MSE Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data/stk&amp;idxready.rda")

aa.stk <- HKE.stk
aa.idx <- HKE.idx
idx <- HKE.idx


HKE.stk <- setPlusGroup(HKE.stk, 7)

# plot(HKE.stk)

# model fitting:
qmod1 <- list(~ factor(age),~ factor(age) )
fmod2 <- ~ factor(age) + s(year, k=4)
srmod1 <- ~ factor(year)

# fit1 <- a4aSCA(stock = HKE.stk, indices = HKE.idx,fmodel=fmod1,
qmodel=qmod1, srmodel=srmod1)
```

```
# fit1 <- a4aSCA(stock = HKE.stk, indices = HKE.idx,fmodel=fmod2,
qmodel=qmod1, srmodel=srmod1) #BetterOne
fit <- a4aSCA(stock = aa.stk, indices = (HKE.idx),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1,verbose = FALSE, fit =
"assessment")

stk1 <- aa.stk + fit

ids <- HKE.idx
ids <- FLIndices(HKE.idx)

stk <-stk1
ids[[1]]@index[ids[[1]]@index == 0] <- 0.1
ids[[1]]@catch.n[ids[[1]]@catch.n == 0] <- 0.1

# plot(stk1) #Good One

ref.points<-brp(FLBRP(stk1))

#============================================================
#BRP
#============================================================
#======================================================================
=========
# Stochastic projections to show example of envelope analysis
#----------------------------------------------------------------------
---------
# Fcurr: 0.8271455
# Btrig: 5331.954
# Bpa: 5331.954
# Blim: 2665.977
# Fmsy: 0.4

# Assign names to tuning indices

it <- 250                              # iterations - should be 250
nit <- 250
y0 <- range(stk)["minyear"]         # year zero (initial) = 1975
ny <- 24                               # number of years to project -
Usually 20
# In order for this code to run iy = dy
dy <- 2015                            # data year
ay <- 2015                            # assessment year
iy <- 2015                           # initial projections year (also
intermediate)
fy <- iy + ny -1                      # final year
vy <- ac(iy:fy)
nsqy <- 3                             # number of SQ years upon which
to average results

mny <- 2020                           #2016 # min year to get to trg
mxy <- 2020                           # 2016 # max year to get to trg

# Management quantities
#flo <- 0.23
#fup <- 0.36
#fmsy <- 0.55
# 1. F status quo: maintain F from 2015
yprec <- brp(FLBRP(stk))
yprec
```

```
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash
# plot(ypr(yprec)~fbar(yprec),type='l')
fsq <- mean(c(fbar(stk1)[,ac(dy)]))
# plot(yprec)
ggsave("YPR.png",last_plot())
fcurr <- mean(harvest(stk)[,3])
blim <- min(ssb(stk1))
bpa <- blim*2
Btrig <- bpa
idx0 <- idx
dt <- date()

# Fill in zeros with small values
catch.n(stk)[catch.n(stk)==0] <- 0.01
for (i in 1:length(idx)){
  index(idx[[i]])[index(idx[[i]])==0] <- 0.01
}

# Expand the objects to the number of iterations
stk <- propagate(stk, fill.iter=T, iter=nit)
# introduce variability in the catch numbers at age
stk@catch.n <- stk@catch.n * exp(rlnorm( prod(dim(stk@catch.n)), 0,
0.2))
stk@catch <- quantSums(catch.n(stk)*catch.wt(stk))
# - index
for (i in 1:length(idx))
  idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=nit)

#----------------------------------------------------------------------
---------
# S/R
#----------------------------------------------------------------------
---------

# sr <- fmle(as.FLSR(sstk, model="geomean"))
sr <- fmle(as.FLSR(stk, model="segreg"), fixed=list(b=mean(ssb(stk))))
# method="L-BFGS-B"mean(ssb(stk))
sr.res <- residuals(sr)
# plot(sr.res)
plot(sr)
a <- as.numeric(sr@params["a"])
b <- as.numeric(sr@params["b"])
rec.res <- residuals(sr)
set.seed(108)
# mean
arima.fit <- arima(an(rec.res), order = c(1, 0, 0))
# create autocorrelation in residuals and propagate throughout stock
into the future
# from initial year of projections (iy) to last of projections (ny-1)
sr.res <- make.arma.resid(arima.fit, age = 0, years = iy:(iy + ny-1),
nit = it)
plot(sr.res)


#----------------------------------------------------------------------
----------
#
#----------------------------------------------------------------------
----------
```

```
# Fixed objects
TAC <- FLQuant(NA, dimnames=list(TAC="all", year=vy, iter=1:it))
BB <- FLQuant(0, dimnames=list(TAC="all", year=vy, iter=1:it))

# # Prepare stock objects we need, with iterations and propagate towards
final year
stk <- iter(aa.stk, 1)
# simulate new stock ased on a4a final fit
sstk <- stk + simulate(fit, it)

summary(sstk)
# plot(sstk)

# short term forecast: start with a projection of F into the future to
ny (16 yrs)
# this serves as a starting point for projecting the stock

pstk <- stf(sstk, ny, 3, 3)              # harvest is average last 3
years

landings.n(pstk) <- propagate(landings.n(pstk), it)
discards.n(pstk) <- propagate(discards.n(pstk), it)

ipy <- (iy+1):range(pstk)["maxyear"]
ly.pos <- (dims(pstk)$year-24+1):dims(pstk)$year

# idx<- ids

# for (i in 1:length(idx))
#   idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=it)

idx <- ids

for (i in 1:length(idx)){
  idx.q <- idx_temp <- FLQuant(NA, dimnames=dimnames(stock.n(pstk)))
  for (it in 1:it) {
    lst <- mcf(list(idx[[i]]@index, stock.n(stk)))
    idx.lq <- iter(log(lst[[1]]/lst[[2]]),it)
    idx.lq[is.infinite(idx.lq)] <- NA # fix zeros
    idx.qmu <- idx.qsig <- stock.n(iter(pstk,1))
    idx.qmu[] <- yearMeans(idx.lq)
    idx.qsig[] <- log((sqrt(yearVars(idx.lq))/yearMeans(idx.lq))^2 + 1)
    idx.q[,ac(y0:dy),,,,it] <- exp(idx.lq[,ac(y0:dy),])
    for (yy in vy)
      idx.q[,yy,,,,it] <- rlnorm(1, idx.qmu[,yy,], idx.qsig[,yy,])
  }
  plot(idx.q)
  idx_temp <- idx.q * stock.n(pstk)
  idx[[i]] <- FLIndex(index=idx_temp, index.q=idx.q)
  range(idx[[i]])[c("startf", "endf")] <- c(0, 0)
  plot(index(idx[[i]]))
}


#-----------------------------------------------------------------------
---------
# 70% Reduction on F
#-----------------------------------------------------------------------
---------
```

```
# Set up the Btrigger (in this case Bpa)
Btrig <- bpa
idx0 <- idx
dt <- date()

##########################################################
# go fish
for(i in vy[-length(vy)]){
  ## i <- vy[-length(vy)][1]
  print(i)
  gc()
  ay <- an(i)   # an is equivalent to as.numeric
  cat(i, "\n")
  vy0 <- 1:(ay-y0) # data years (positions vector)
  sqy <- (ay-y0-nsqy+1):(ay-y0) # status quo years (positions vector)
  stk0 <- pstk[,vy0]
  catch.n(stk0) <- catch.n(stk0) + 1 # avoid zeros
  ## note that vy0 is changing below so index is being updated
  for (index_counter in 1:length(idx)){
    idx0[[index_counter]] <- idx[[index_counter]][,vy0]
    index(idx[[index_counter]])[,i]                          <-
stock.n(pstk)[,i]*index.q(idx[[index_counter]])[,i] + 1
  }
  ##
  qmod1 <- list(~ factor(age),~ factor(age) )
  fmod2 <- ~ factor(age) + s(year, k=4)
  srmod1 <- ~ factor(year)
  fit            <-            sca(stk0,            FLIndices(idx0),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1)
  stk0 <- stk0 + fit
  # fwd control
  fsq0 <- yearMeans(fbar(stk0)[,c(sqy)])
  dnms <- list(iter=1:it, year=c(ay, ay + 1), c("min", "val", "max"))
  arr0 <- array(NA, dimnames=dnms, dim=unlist(lapply(dnms, length)))
  ## ftrg.vec <- rep(ftrg, it) ## original
  #refpt <- data.frame(ssb = 1, harvest = 1)
  #ftrg.q <- hcr.nocheck.GFCM.f(ssb(stk0)[, ac(an(i) - 1)], Fsq0=fsq0,
refpt = refpt, Btrig = Btrig, Fmin = 0, Blim = blim, Bpa=bpa)
  #ftrg.q <- hcr.nocheck(ssb(stk0)[, ac(an(i) - 1)], refpt = refpt, Ftar
= ftrg, Btrig = bpa, Fmin = 0, Blim = blim)
  #ftrg.vec <- an(ftrg.q)
  #Bescape <- blim
  ftrg.q <- fbar(stk1)[,"2015",,,,] * 0.7
  ftrg.vec <- rep(an(ftrg.q),it)
  arr0[,,"val"] <- c(fsq0, ftrg.vec) #rep(NA, it)
  arr0[,,"min"] <- c(rep(NA, 2 * it))
  arr0 <- aperm(arr0, c(2,3,1))
  ctrl <- fwdControl(data.frame(year=c(ay, ay+1), quantity=c('f', 'f'),
val=NA))
  ctrl@trgtArray <- arr0
  #future_catch <- c(catch(stk0)[,"2013"]) * 0.9
  #ctrl_catch  <-  fwdControl(data.frame(year=an(ay:(ay+1)),  quantity  =
"catch", val=future_catch))
  #ctrl_target <- ctrl_target[order(ctrl_target$year),]
  #ctrl <- fwdControl(ctrl_catch)
  #ctrl   <-   fwdControl(data.frame(year=c(ay,   ay+1,   ay   +   3),
quantity=c('f', 'f', 'ssb'), val=NA))
  #ctrl@trgtArray <- arr0
  ##
```

```
  stkTmp <- stf(stk0, 2)
  stkTmp <- fwd(stkTmp, ctrl=ctrl, sr=sr, sr.residuals = exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals = exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #sr.residuals = exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE
  ## USING F
  TAC[,ac(ay+1)] <- catch(stkTmp)[,ac(ay+1)]
  # OM proj
  ctrl@target <- ctrl@target[2,]
  ## original was catch
  ##ctrl@target[,"quantity"] <- "catch"
  ctrl@trgtArray <- ctrl@trgtArray[2,,,drop=FALSE]
  ## original was catch
  ##ctrl@trgtArray[,"val",] <- c(TAC[,ac(ay+1)]) #+ BB[,ac(ay)])
  pstk <- fwd(pstk, ctrl=ctrl, sr=sr, sr.residuals = exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals = exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals = exp(sr.res[,ac(ay+1)]), sr.residuals.mult = TRUE
  #BB[,ac(ay+1)] <- iterMedians(TAC[,ac(ay+1)]) - catch(pstk)[,ac(ay+1)]
}

return(val)
date()

nstk <- pstk

plot(window(nstk, end=2037))
# ssb(pstk)[,"2024"]
# hist(ssb(pstk)[,"2024"])
#
# # Proportion below Blim - are you less than 5%
# sum(ssb(pstk)[,"2030"] < blim) / it

######################################################################
#########################
######################################################################
#########################
# FMSY
######################################################################
#########################
######################################################################
#########################

##################################################
###                                            ###
###                MSE - FMSY                  ###
###            a4a - deterministic             ###
##################################################


rm(list=ls())
cat("\014")
#

library(FLa4a)
library(FLash)
library(FLAssess)
library(ggplotFL)
library(FLBRP)
```

```
library(FLSAM)
library(FLCore)
library(FLEDA)
library(FLXSA)
library(SQLiteFL)
library(doBy)
library(reshape)
library(devtools)
library(msy)

setwd("~/MSE      Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data")

source('~/MSE     Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Scripts/MSE_funs2017.R')

load("~/MSE       Project/MSE/2017/StraitOfSicily/HKE/a4a/Deterministic
a4a/Data/stk&amp;idxready.rda")

aa.stk <- HKE.stk
aa.idx <- HKE.idx
idx <- HKE.idx


HKE.stk <- setPlusGroup(HKE.stk, 7)

# plot(HKE.stk)

# model fitting:
qmod1 <- list(~ factor(age),~ factor(age) )
fmod2 <- ~ factor(age) + s(year, k=4)
srmod1 <- ~ factor(year)

#  fit1  <-  a4aSCA(stock  =  HKE.stk,  indices  =  HKE.idx,fmodel=fmod1,
qmodel=qmod1, srmodel=srmod1)
#  fit1  <-  a4aSCA(stock  =  HKE.stk,  indices  =  HKE.idx,fmodel=fmod2,
qmodel=qmod1, srmodel=srmod1) #BetterOne
fit    <-    a4aSCA(stock    =    aa.stk,    indices    =    (HKE.idx),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1,verbose   =   FALSE,   fit   =
"assessment")

stk1 <- aa.stk + fit

ids <- HKE.idx
ids <- FLIndices(HKE.idx)

stk <-stk1
ids[[1]]@index[ids[[1]]@index == 0] <- 0.1
ids[[1]]@catch.n[ids[[1]]@catch.n == 0] <- 0.1

# plot(stk1) #Good One

ref.points<-brp(FLBRP(stk1))

#==========================================================
#BRP
#==========================================================
#====================================================================
=========
# Stochastic projections to show example of envelope analysis
```

```
#---------------------------------------------------------------------
---------
# Fcurr: 0.8271455
# Btrig: 5331.954
# Bpa: 5331.954
# Blim: 2665.977
# Fmsy: 0.4

# Assign names to tuning indices

it <- 250                                # iterations - should be 250
nit <- 250
y0 <- range(stk)["minyear"]         # year zero (initial) = 1975
ny <- 24                                 # number of years to project -
Usually 20
# In order for this code to run iy = dy
dy <- 2015                              # data year
ay <- 2015                              # assessment year
iy <- 2015                             # initial projections year (also
intermediate)
fy <- iy + ny -1                        # final year
vy <- ac(iy:fy)
nsqy <- 3                               # number of SQ years upon which
to average results

mny <- 2020                             #2016 # min year to get to trg
mxy <- 2020                             # 2016 # max year to get to trg

# Management quantities
#flo <- 0.23
#fup <- 0.36
#fmsy <- 0.55
# 1. F status quo: maintain F from 2015
yprec <- brp(FLBRP(stk))
yprec
refpts(yprec)
refpts(yprec)<-refpts(yprec)[c(4)]#without F crash
# plot(ypr(yprec)~fbar(yprec),type='l')
fsq <- mean(c(fbar(stk1)[,ac(dy)]))
plot(yprec)
ggsave("YPR.png",last_plot())
fcurr <- mean(harvest(stk)[,3])
blim <- min(ssb(stk1))
bpa <- blim*2
Btrig <- bpa
idx0 <- idx
dt <- date()

# Fill in zeros with small values
catch.n(stk)[catch.n(stk)==0] <- 0.01
for (i in 1:length(idx)){
  index(idx[[i]])[index(idx[[i]])==0] <- 0.01
}

# Expand the objects to the number of iterations
stk <- propagate(stk, fill.iter=T, iter=nit)
# introduce variability in the catch numbers at age
stk@catch.n  <-  stk@catch.n  *  exp(rlnorm(  prod(dim(stk@catch.n)),  0,
0.2))
stk@catch <- quantSums(catch.n(stk)*catch.wt(stk))
```

```
# - index
for (i in 1:length(idx))
  idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=nit)

#----------------------------------------------------------------------
---------
# S/R
#----------------------------------------------------------------------
---------

# sr <- fmle(as.FLSR(sstk, model="geomean"))
sr <- fmle(as.FLSR(stk, model="segreg"), fixed=list(b=mean(ssb(stk))))
# method="L-BFGS-B"mean(ssb(stk))
sr.res <- residuals(sr)
# plot(sr.res)
plot(sr)
a <- as.numeric(sr@params["a"])
b <- as.numeric(sr@params["b"])
rec.res <- residuals(sr)
set.seed(108)
# mean
arima.fit <- arima(an(rec.res), order = c(1, 0, 0))
# create autocorrelation in residuals and propagate throughout stock
into the future
# from initial year of projections (iy) to last of projections (ny-1)
sr.res <- make.arma.resid(arima.fit, age = 0, years = iy:(iy + ny-1),
nit = it)
plot(sr.res)


#----------------------------------------------------------------------
----------
#
#----------------------------------------------------------------------
----------

# Fixed objects
TAC <- FLQuant(NA, dimnames=list(TAC="all", year=vy, iter=1:it))
BB <- FLQuant(0, dimnames=list(TAC="all", year=vy, iter=1:it))

# # Prepare stock objects we need, with iterations and propagate towards
final year
stk <- iter(aa.stk, 1)
# simulate new stock ased on a4a final fit
sstk <- stk + simulate(fit, it)

summary(sstk)
plot(sstk)

# short term forecast: start with a projection of F into the future to
ny (16 yrs)
# this serves as a starting point for projecting the stock

pstk <- stf(sstk, ny, 3, 3)               # harvest is average last 3
years

landings.n(pstk) <- propagate(landings.n(pstk), it)
discards.n(pstk) <- propagate(discards.n(pstk), it)

ipy <- (iy+1):range(pstk)["maxyear"]
```

```
ly.pos <- (dims(pstk)$year-24+1):dims(pstk)$year

# idx<- ids

# for (i in 1:length(idx))
#   idx[[i]] <- propagate(idx[[i]], fill.iter=T, iter=it)

idx <- ids

for (i in 1:length(idx)){
  idx.q <- idx_temp <- FLQuant(NA, dimnames=dimnames(stock.n(pstk)))
  for (it in 1:it) {
    lst <- mcf(list(idx[[i]]@index, stock.n(stk)))
    idx.lq <- iter(log(lst[[1]]/lst[[2]]),it)
    idx.lq[is.infinite(idx.lq)] <- NA # fix zeros
    idx.qmu <- idx.qsig <- stock.n(iter(pstk,1))
    idx.qmu[] <- yearMeans(idx.lq)
    idx.qsig[] <- log((sqrt(yearVars(idx.lq))/yearMeans(idx.lq))^2 + 1)
    idx.q[,ac(y0:dy),,,,it] <- exp(idx.lq[,ac(y0:dy),])
    for (yy in vy)
      idx.q[,yy,,,,it] <- rlnorm(1, idx.qmu[,yy,], idx.qsig[,yy,])
  }
  plot(idx.q)
  idx_temp <- idx.q * stock.n(pstk)
  idx[[i]] <- FLIndex(index=idx_temp, index.q=idx.q)
  range(idx[[i]])[c("startf", "endf")] <- c(0, 0)
  plot(index(idx[[i]]))
}


# Set up the Btrigger (in this case Bpa)
Btrig <- bpa
idx0 <- idx
dt <- date()

#########################################################
# go fish
for(i in vy[-length(vy)]){
  ## i <- vy[-length(vy)][1]
  print(i)
  gc()
  ay <- an(i)   # an is equivalent to as.numeric
  cat(i, "\n")
  vy0 <- 1:(ay-y0) # data years (positions vector)
  sqy <- (ay-y0-nsqy+1):(ay-y0) # status quo years (positions vector)
  stk0 <- pstk[,vy0]
  catch.n(stk0) <- catch.n(stk0) + 1 # avoid zeros
  ## note that vy0 is changing below so index is being updated
  for (index_counter in 1:length(idx)){
    idx0[[index_counter]] <- idx[[index_counter]][,vy0]
    index(idx[[index_counter]])[,i]                            <-
stock.n(pstk)[,i]*index.q(idx[[index_counter]])[,i] + 1
  }
  ##
  qmod1 <- list(~ factor(age),~ factor(age) )
  fmod2 <- ~ factor(age) + s(year, k=4)
  srmod1 <- ~ factor(year)
  fit            <-           sca(stk0,            FLIndices(idx0),
fmodel=fmod2,qmodel=qmod1,srmodel=srmod1)
  stk0 <- stk0 + fit
```

```
  # fwd control
  fsq0 <- yearMeans(fbar(stk0)[,c(sqy)])
  dnms <- list(iter=1:it, year=c(ay, ay + 1), c("min", "val", "max"))
  arr0 <- array(NA, dimnames=dnms, dim=unlist(lapply(dnms, length)))
  ## ftrg.vec <- rep(ftrg, it) ## original
  #refpt <- data.frame(ssb = 1, harvest = 1)
  #ftrg.q <- hcr.nocheck.GFCM.f(ssb(stk0)[, ac(an(i) - 1)], Fsq0=fsq0,
refpt = refpt, Btrig = Btrig, Fmin = 0, Blim = blim, Bpa=bpa)
  #ftrg.q <- hcr.nocheck(ssb(stk0)[, ac(an(i) - 1)], refpt = refpt, Ftar
= ftrg, Btrig = bpa, Fmin = 0, Blim = blim)
  #ftrg.vec <- an(ftrg.q)
  #Bescape <- blim
  ftrg.q <- fbar(stk1)[,"2015",,,,]/4.875 #fbar/F0.1
  ftrg.vec <- rep(an(ftrg.q),it)
  arr0[,,"val"] <- c(fsq0, ftrg.vec) #rep(NA, it)
  arr0[,,"min"] <- c(rep(NA, 2 * it))
  arr0 <- aperm(arr0, c(2,3,1))
  ctrl <- fwdControl(data.frame(year=c(ay, ay+1), quantity=c('f', 'f'),
val=NA))
  ctrl@trgtArray <- arr0
  #future_catch <- c(catch(stk0)[,"2013"]) * 0.9
  #ctrl_catch <- fwdControl(data.frame(year=an(ay:(ay+1)), quantity =
"catch", val=future_catch))
  #ctrl_target <- ctrl_target[order(ctrl_target$year),]
  #ctrl <- fwdControl(ctrl_catch)
  #ctrl   <-   fwdControl(data.frame(year=c(ay,   ay+1,   ay   +   3),
quantity=c('f', 'f', 'ssb'), val=NA))
  #ctrl@trgtArray <- arr0
  ##
  stkTmp <- stf(stk0, 2)
  stkTmp   <-   fwd(stkTmp,   ctrl=ctrl,   sr=sr,   sr.residuals   =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE
  ## USING F
  TAC[,ac(ay+1)] <- catch(stkTmp)[,ac(ay+1)]
  # OM proj
  ctrl@target <- ctrl@target[2,]
  ## original was catch
  ##ctrl@target[,"quantity"] <- "catch"
  ctrl@trgtArray <- ctrl@trgtArray[2,,,drop=FALSE]
  ## original was catch
  ##ctrl@trgtArray[,"val",] <- c(TAC[,ac(ay+1)]) #+ BB[,ac(ay)])
  pstk    <-    fwd(pstk,    ctrl=ctrl,    sr=sr,    sr.residuals    =
exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay:(ay+1))]), sr.residuals.mult = TRUE) #, sr.residuals
= exp(sr.res[,ac(ay+1)]), sr.residuals.mult = TRUE
  #BB[,ac(ay+1)]        <-        iterMedians(TAC[,ac(ay+1)])        -
catch(pstk)[,ac(ay+1)]
}

return(val)
date()

nstk <- pstk

plot(window(nstk, end=2037))
```

```
# SCRIPT INDEX (GENERAL)

# install.packages(c("copula","triangle"))
#    install.packages(c("FLCore",    "FLa4a"),    repos="http://flr-
project.org/R")

library(FLa4a)
library(XML)
library(reshape2)
library(plot3D)
library(FLCore)
library(FLXSA)
library(ggplotFL)

#
rm(list=ls())
cat("\014")
#

setwd("~/MSE         Project/MSE/2017/StraitOfSicily/HKE/a4a/Stochastic
a4a/Data")

#setwd("~/HAKE 12-16/MSE-StrategyXSA/Length structured")

######################################################################
###########
##                                                                  ##
##                            Functions                             ##
##                                                                  ##
######################################################################
###########

# recode Gadget's length categories
qt2qt <- function(object, id=5, split="-"){
  qt <- object[,id]
  levels(qt) <- unlist(lapply(strsplit(levels(qt), split=split), "[[",
2))
  as.numeric(as.character(qt))
}
# function to check import and do some massage
cim <- function(object, n, wt, hrv="missing"){
  v <- object[sample(1:nrow(object), 1),]
  c1                                                                <-
c(n[as.character(v$V5),as.character(v$V1),1,as.character(v$V2)]==v$V6)
  c2                                                                <-
c(wt[as.character(v$V5),as.character(v$V1),1,as.character(v$V2)]==v$V7
)
  if(missing(hrv)){
    c1 + c2 == 2
  } else {
    c3                                                              <-
c(hrv[as.character(v$V5),as.character(v$V1),1,as.character(v$V2)]==v$V
8)
    c1 + c2 + c3 == 3
  }
}
# plot for S4 data structures with diagram
```

```
plotS4 <- function(object, linktext="typeof", main="S4 class", ...){
  6
  args <- list(...)
  obj <- getClass(as.character(object))
  df0  <-  data.frame(names(obj@slots),  unlist(lapply(obj@slots,  "[[",
1)))
  nms <- c(t(df0))
  nslts <- length(nms)/2
  M <- matrix(nrow = length(nms), ncol = length(nms), byrow = TRUE, data
= 0)
  for(i in 1:nslts){
    M[i*2,i*2-1] <- linktext
  }
  args$A=M
  args$pos=rep(2, length(nms)/2)
  args$name = nms
  args$main=main
  do.call("plotmat", args)
}

######################################################################
###########
##                                                                    ##
##                       Introducing Data                             ##
##                                                                    ##
######################################################################
###########


# Catch

cth.orig        <-        read.table("cth_mean_weight_kg_review.txt",
header=FALSE,skip=5,fill = TRUE)
head(cth.orig)
cth.orig[,5] <- qt2qt(cth.orig)
cth.n <- acast(V5~V1~1~V2~1~1, value.var="V6", data=cth.orig)
cth.wt <- acast(V5~V1~1~V2~1~1, value.var="V7", data=cth.orig)
dnms <- dimnames(cth.n)
names(dnms) <- names(dimnames(FLQuant()))
names(dnms)[1] <- "len"
cth.n <- FLQuant(cth.n, dimnames=dnms)
cth.wt <- FLQuant(cth.wt, dimnames=dnms)

HKE.stk <- FLStockLen(catch.n=cth.n,
                      catch.wt=cth.wt)

cim(cth.orig,cth.n,cth.wt)

HKE.stk <- FLStockLen(catch.n=cth.n,catch.wt=cth.wt)

# Survey

idx.orig <- read.table("idx_mean_weight_kg.txt", skip=5, header=FALSE,
fill = TRUE)
idx.orig[,5] <- qt2qt(idx.orig)
idx.n <- acast(V5~V1~1~V2~1~1, value.var="V6", data=idx.orig)
idx.wt <- acast(V5~V1~1~V2~1~1, value.var="V7", data=idx.orig)
dnms <- dimnames(idx.n)
names(dnms) <- names(dimnames(FLQuant()))
names(dnms)[1] <- "len"
```

```
idx.n <- FLQuant(idx.n, dimnames=dnms)
idx.wt <- FLQuant(idx.wt, dimnames=dnms)
HKE.idx <- FLIndex(index=idx.n, catch.n=idx.n, catch.wt=idx.wt)
effort(HKE.idx)[] <- 100


m(HKE.stk)[]<-0.05
mat(HKE.stk)[]<-m.spwn(HKE.stk)[]<-harvest.spwn(HKE.stk)[]<-0

## careful, landings are not retained in the stock object after length
to age conversion
landings(HKE.stk)[]<-
c(3792.2,3395.5,3284.4,3444.7,2532.8,3306.1,3467.4,4415.0,4081.8)

######################################################################
###########
##                                                                  ##
##              Adding uncertainty to growth parameters             ##
##                                                                  ##
######################################################################
###########

#Von Bert. Model

vbObj <- a4aGr(
  grMod=~linf*(1-exp(-k*(t-t0))),
  grInvMod=~t0-1/k*log(1-len/linf),
  params=FLPar(linf=100, k=0.116, t0=-0.6, units=c("cm","ano-1","ano"))
)

lc=100
predict(vbObj, len=lc)

predict(vbObj, t=predict(vbObj, len=lc))

predict(vbObj, len=5:20+0.5)
predict(vbObj, t=1:20+0.5)

prediction <- predict(vbObj, len=seq(8, 74, length = 200))

predictiontime <- predict(vbObj, t=seq(0.1,10, length=200))

plot(seq(8, 74, length = 200), prediction, xlab="length (cm)", ylab="Age
(years)")

plot(seq(0.1,10,  length=200),  predictiontime,  ylab="length  (cm)",
xlab="Age (years)")

##############################################
##                                          ##
## Ages without uncertainty:                ##
## cth.n <- l2a(catch.n(HKE.stk), vbObj)    ##
##                                          ##
##############################################

# 3.2.- AÑADIENDO INCERTIDUMBRE CON LA DISTRIBUCIÓN NORMAL MULTIVARIANTE
# Adding uncertainty with a normal multivariate distribution
cm <- diag(c(1,1,1))

cm[1,2] <- cm[2,1] <- -0.5
```

```
cv <- 0.2

p <- c(linf=100, k=0.116, t0=-0.6)
vc <- matrix(1, ncol=3, nrow=3)
l <- vc
l[1,] <- l[,1] <- p[1]*cv
k <- vc
k[,2] <- k[2,] <- p[2]*cv
t <- vc
t[3,] <- t[,3] <- p[3]*cv
mm <- t*k*l
diag(mm) <- diag(mm)^2
mm <- mm*cm


all.equal(cm, cov2cor(mm)) # Correlation = "True"

vbObj <- a4aGr(grMod=~linf*(1-exp(-k*(t-t0))),
               grInvMod=~t0-1/k*log(1-len/linf),
               params=FLPar(linf=p["linf"],    k=p["k"],    t0=p["t0"],
units=c("cm","ano-1","ano")), vcov=mm)

# Data is following a normal multivariate distribution

vbObj@params

dim(vbObj@params)

# Simulating 1000 iterations:

vbNorm <- mvrnorm(100,vbObj)

vbNorm@params

dim(vbNorm@params)

ages <- predict(vbNorm, len=5:10+0.5)
dim(ages)

ages[,1:10]

par(mfrow=c(1,1))
hist(c(params(vbNorm)["linf",]), main="linf", xlab="")
hist(c(params(vbNorm)["k",]), main="k", prob=TRUE, xlab="")
hist(c(params(vbNorm)["t0",]), main="t0", xlab="")

splom(data.frame(t(params(vbNorm)@.Data)),
pch=".",par.settings=list(plot.symbol=list(pch=50, cex=1.5, col=1)))

boxplot(t(predict(vbNorm, t=0:25+0.5)),xlab="Years",ylab="Length")

######################################################################
###########
##                                                                  ##
##                Natural Mortality matrix uncertainty              ##
##                                                                  ##
######################################################################
###########
```

```
shape4 <- FLModelSim(model=~exp(-age-0.5))
level4 <- FLModelSim(model=~k^0.66*t^0.57,
                     params=FLPar(k=0.116, t=10),
                     vcov=array(c(0.002, 0.01,0.01, 1), dim=c(2,2)))
trend4      <-      FLModelSim(model=~1+b,      params=FLPar(b=0.5),
vcov=matrix(0.02))

m4 <- a4aM(shape=shape4, level=level4, trend=trend4)
m4 <- mvrnorm(100,m4)
m4
m4@level
params(trend(m4))
m4                        <-                        a4aM(shape=shape4,
level=mvrnorm(100,level4),trend=mvrnorm(100,trend4))
params(shape(m4))

#

linf <- 100
k <- 0.116

mm <- matrix(NA, ncol=2, nrow=2)
diag(mm) <- c((linf*0.1)^2,(k*0.1)^2)
mm[upper.tri(mm)] <- mm[lower.tri(mm)] <- c(0.05)

cov2cor(mm)

mgis2                                                               <-
FLModelSim(model=~k*(linf/len)^1.5,params=FLPar(linf=linf,k=k),vcov=mm
)
pars <- list(list(a=90,b=110), list(a=0.05,b=0.15,c=0.110))
mgis2 <- mvrtriangle(100, mgis2, paramMargins=pars)
mgis2

par(mfrow=c(1,1))
hist(c(params(mgis2)["linf",]), main="linf", xlab="")
hist(c(params(mgis2)["k",]), main="k", prob=TRUE, xlab="")
splom(data.frame(t(params(mgis2)@.Data)),
pch=".",par.settings=list(plot.symbol=list(pch=50, cex=1.5, col=1)))

m5<-m4
shape(m5) <- mgis2

m(m5, nao=1)
dim(m(m5, nao=1))

m(m4)

rngquant(m4)<-c(0,6)
dim(m(m4))
m(m4)

rngyear(m4)<-c(2007,2015)
m(m4)
dim(m(m4))

flq <- m(m4)

bwplot(data~factor(age)|year,
       data=flq,
```

```
       par.settings=list(plot.symbol=list(cex=0.2, col="gray50"),
                         box.umbrella=list(col="gray40"),
                         box.rectangle=list(col="gray30")),
       ylab="M", xlab="age (years)", scales=list(x=list(rot=90)))


################################################################
###########
##                                                            ##
##                    Reading the XSA object                  ##
##       (to get assumptions on natural mortality and maturity at age)
##
##                                                            ##
################################################################
###########

## XSA object is ages 1 to 7
aaXSA.stk                    <-                    readFLStock("~/MSE
Project/MSE/2017/StraitOfSicily/HKE/a4a/Stochastic
a4a/Data/HKE1216.IND", no.discards=TRUE) #only commercial data
aaXSA.stk <- trim(aaXSA.stk, age=0:6)

aaXSA.idx                   <-                   readFLIndices("~/MSE
Project/MSE/2017/StraitOfSicily/HKE/a4a/Stochastic
a4a/Data/TUNEFF.DAT")
name(aaXSA.idx[[1]]) <- "MEDITS_12-16"

# Length to age

aStk <- l2a(HKE.stk, vbNorm, plusgroup=6) #
aIdx <- l2a(HKE.idx, vbNorm) #

# Intro M into the object:

# mortalidad <- trim(m(m4), age=1:6)

# aStk@m <- mortalidad


####

# aStk@m <- m(m4)

#aStk <- trim(aStk, age=1:6)
units(aStk)[1:17]    <- as.list(c(rep(c("tonnes","thousands","kg"),4),
                              rep("NA",2),"f",rep("NA",2)))
aStk@discards.n[]      <- 0; aStk@discards.wt[] <- 0; aStk@discards <-
computeDiscards(aStk)

landings(aStk)[]<-
c(3792.2,3395.5,3284.4,3444.7,2532.8,3306.1,3467.4,4415.0,4081.8)

catch(aStk)[]<-computeCatch(aStk)

## we need to check SOP correction
(catch(aStk)-landings(aStk))/landings(aStk)*100

## PROBLEM! for now assuming landings = computed catches (catch.n *
catch.wt)
```

```
aStk@catch.n[aStk@catch.n==0] <- 0.001


landings(aStk)<-catch(aStk)
landings.n(aStk) <- catch.n(aStk)
landings.wt(aStk) <-catch.wt(aStk)
stock.wt(aStk) <- catch.wt(aStk)

dim(aaXSA.stk@m)
dim(aStk@m)

#aStk@m<- aaXSA.stk@m
#aStk@mat <- aaXSA.stk@mat
#aStk@m.spwn <- aaXSA.stk@m.spwn


## using same m, maturity ogive, m.spawn as in XSA assessment
my.iter = 100
for (i in 1:my.iter){
  #aStk@m[,,,,,i]<- aaXSA.stk@m
  #aStk@mat[,,,,,i] <- aaXSA.stk@mat
  aStk@m.spwn[,,,,,i] <- aaXSA.stk@m.spwn
  aStk@harvest.spwn[,,,,,i] <- aaXSA.stk@harvest.spwn
}


range(aStk)["minfbar"] <- 2
range(aStk)["maxfbar"] <- 4
aStk <- trim(aStk, age=1:6)


aIdx@catch.n <- aIdx@index
aIdx <- trim(aIdx, age=1:6)
aIdx@range["plusgroup"] <- 6

aIdx@index[aIdx@index==0] <- 0.001
aIdx@catch.n[aIdx@catch.n==0] <- 0.001


range(aIdx)[c("startf", "endf")] <- c(2,4)

# aStk@range["min"] <- 1


summary(aIdx)
summary(aStk)

fmod <- ~factor(age) + factor(year)
qmod <- list(~s(age, k=4))
n1mod <- ~s(age,k=5)

# Tests

fit <- a4aSCA(aStk,FLIndices(aIdx),fmodel=~factor(age) + factor(year))
out <- aStk + fit

plot(out)

# MSE -
```

```
library(FLCore)
library(FLAssess)
library(FLash)

?stf



hke_stf <- stf(out, nyears = 3,wts.nyears=4, fbar.nyears=3) #wts.nyrs:
Number of years over which to calculate mean for *.wt, *.spwn, mat and
m slots.
summary(hke_stf)
stock.wt(hke_stf)
fbar(hke_stf)
ssb(hke_stf)

library("FLBRP")
ref.points<-brp(FLBRP(out))
ref.points@refpts

# SR-

sr <- fmle(as.FLSR(out, model="segreg")) # bevholt, ricker
plot(sr)

# Short term

f_future <- (0.61)

ctrl_target <- data.frame(year = 2016:2018,
                          quantity = "f",
                          val = c(f_future, f_future, f_future))

ctrl_f <- fwdControl(ctrl_target)
ctrl_f
slotNames(ctrl_f)
ctrl_f@target

hke_fwd_f <- fwd(hke_stf, ctrl = ctrl_f, sr = sr)

fbar(hke_fwd_f)
f_future
ssb(hke_fwd_f)
plot(window(hke_fwd_f, start = 2007, end = 2018))

# Status Quo - Final

yrs <- 2016:2036

f0.1 <- 0.64
hke_stf_long <-stf(out, length(yrs))

ctrl <- fwdControl(
  data.frame(year =rep(yrs, each=2),
             rel.year=rep(c(0,NA),length(yrs))+rep(yrs-1,each=2),
             val =rep(c(.2, NA), length(yrs)),
             min =rep(c(NA, f0.1), length(yrs)),
             quantity="f"))

ctrl
```

```
recovery<-fwd(hke_stf_long, ctrl=ctrl, sr=sr)
fbar(recovery)

plot(window(recovery, start = 2008, end = 2037))

# F0.1 - Final

yrs <- 2016:2036

f0.1 <- 0.17
hke_stf_long <-stf(out, length(yrs))

ctrl <- fwdControl(
  data.frame(year =rep(yrs, each=2),
             rel.year=rep(c(0,NA),length(yrs))+rep(yrs-1,each=2),
             val =rep(c(.2, NA), length(yrs)),
             min =rep(c(NA, f0.1), length(yrs)),
             quantity="f"))

ctrl
recovery<-fwd(hke_stf_long, ctrl=ctrl, sr=sr)
fbar(recovery)

plot(window(recovery, start = 2008, end = 2037))

# 70% F - Final

yrs <- 2016:2036

f0.1 <- 0.64 * 0.3
hke_stf_long <-stf(out, length(yrs))

ctrl <- fwdControl(
  data.frame(year =rep(yrs, each=2),
             rel.year=rep(c(0,NA),length(yrs))+rep(yrs-1,each=2),
             val =rep(c(.2, NA), length(yrs)),
             min =rep(c(NA, f0.1), length(yrs)),
             quantity="f"))

ctrl
recovery<-fwd(hke_stf_long, ctrl=ctrl, sr=sr)
fbar(recovery)

plot(window(recovery, start = 2008, end = 2037))

# 50% F - Final

yrs <- 2016:2036

f0.1 <- 0.64 * 0.5
hke_stf_long <-stf(out, length(yrs))

ctrl <- fwdControl(
  data.frame(year =rep(yrs, each=2),
             rel.year=rep(c(0,NA),length(yrs))+rep(yrs-1,each=2),
             val =rep(c(.2, NA), length(yrs)),
             min =rep(c(NA, f0.1), length(yrs)),
             quantity="f"))

ctrl
```

```
recovery<-fwd(hke_stf_long, ctrl=ctrl, sr=sr)
fbar(recovery)

plot(window(recovery, start = 2008, end = 2037))

# 90% F - Final

yrs <- 2016:2036

f0.1 <- 0.64 * 0.1
hke_stf_long <-stf(out, length(yrs))

ctrl <- fwdControl(
  data.frame(year =rep(yrs, each=2),
             rel.year=rep(c(0,NA),length(yrs))+rep(yrs-1,each=2),
             val =rep(c(.2, NA), length(yrs)),
             min =rep(c(NA, f0.1), length(yrs)),
             quantity="f"))

ctrl
recovery<-fwd(hke_stf_long, ctrl=ctrl, sr=sr)
fbar(recovery)

plot(window(recovery, start = 2008, end = 2037))

# END - 22/02/2017
```

Annex – Codes Chapter 2

All code done during the investigation could be found in:

https://gitlab.com/Edusanlla/HCR-TFM

Universitat d'Alacant
Universidad de Alicante

GOBIERNO DE ESPAÑA

MINISTERIO DE AGRICULTURA, ALIMENTACIÓN Y MEDIO AMBIENTE

CIHEAM

El Máster Internacional en GESTIÓN PESQUERA SOSTENIBLE está organizado conjuntamente por la Universidad de Alicante (UA), el Ministerio de Agricultura, Alimentación y Medio Ambiente (MAGRAMA), a través de la Secretaría General de Pesca (SGP), y el Centro Internacional de Altos Estudios Agronómicos Mediterráneos (CIHEAM), a través del Instituto Agronómico Mediterráneo de Zaragoza (IAMZ).

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The Master is developed over two academic years. Upon completion of the first year (a programme based on lectures, practicals, supervised work, seminars and technical visits), during the second part the participants devote a period of 10 months to initiation to research or to professional activities conducting an original research work through the elaboration of the Master Thesis. The present manuscript is the result of one of these works and has been defended before an examination board.